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ILMENAU

The Integration of Device-to-Device Communication in Future Cellular Systems

Dissertation

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by M.Sc. Ali Haider Mahdi
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Zur Erlangung des akademischen Grades
Doktoringenieur (Dr.-Ing.)

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von M.Sc. Ali Haider Mahdi
geboren am 31. 08. 1980 in Bagdad, Irak

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Abstract

The usage of mobile data services over cellular spectrum has been dramatically increased in the last decade. The increment led to an explosive growth in user's booming data demands over the cellular spectrum band. However, the current technologies have a limitation in the allocated spectrum resources, compared to the data demands. This leads to insufficient throughput using the current technologies in the next few years.

Improving the throughput with user's data demands necessitates finding an efficient approach to offload data booming. Device-to-Device (D2D) communication has been proposed as an unconventional mobile paradigm with a scalable manner to offload the mobile data traffic of the local peer-to-peer mobile users by sharing the resources the cellular networks without traversing the base stations. Applying such paradigm increases the spectrum utilization which improves the total throughput in a given cell. However, many issues negatively influence the performance of D2D communication over the cellular spectrum band such as interference from the cellular users, the low activity of the cellular users over the allocated resources in time which reduces spectrum utilization and the dynamic cellular environment which impacts the link performance of D2D communication and may leads to not meet the desired quality of service requirements of the data services.

Solving the aforementioned issues requires: i) developing the appropriate access paradigmas of the D2D communication to meet the desired quality of service requirements of mobile data services; ii) increasing the spectrum utilization of licensed band by enabling unlicensed users to invest the spectrum holes; and iii) developing the link adaptation processes to overcome the dynamic behavior of the cellular system and improve the throughput in D2D communication links.

This dissertation presents the aforementioned solutions for the D2D communication which improve the total throughput in the cell. The dissertation has three main contributions: i) position-based hybrid access paradigm for D2D communication; ii) hybrid access paradigm for unlicensed peer-to-peer users (unlicensed D2D communication); and iii) an algorithm for link adaptation of unlicensed D2D communication.

First, the thesis develops a position-based model for maximizing the throughput of D2D communication using different access paradigms. This model defines the regions in the cell in which the D2D communication can be performed with the desired QoS. Then, a position-based hybrid access paradigm is presented which selects a given access

paradigm used by D2D pairs in order to improve the total throughput in the cell. The proposed access paradigms are evaluated using numerical simulations and the results show improvements in the total throughput and the number of satisfied D2D communications in the cell, compared to recent access paradigms.

Second, an integration of cognitive radio technology with the unlicensed D2D pairs to apply dynamic spectrum access is presented. The recent access paradigms of cognitive radio and their achievable throughput are studied. Then, a position-based hybrid access paradigm is introduced to increase the regions of unlicensed D2D communication. The evaluation of the proposed access paradigm is performed using numerical simulations. The results show improvement in the throughput over the cell and the area used by unlicensed D2D communications, compared to recent access paradigms.

Third, the dynamic behavior of the cellular environment and its interaction with the unlicensed D2D communication is studied. One possible solution presented applying artificial intelligence technique as a cognitive engine to perform link adaptation efficiently. Based on this study, a Self-Organized Link Adaptation (SOLinA) algorithm is presented to adapt the link of unlicensed D2D communication autonomously and determine the link configuration which improves the throughput of the system. The evaluation of the proposed algorithm is performed using simulations of unlicensed D2D communication within dynamic cellular environment. The results of the simulations show that SOLinA outperforms the previous work in the throughput under different separations between the unlicensed D2D communication, different cellular system requirements and at different user's positions in the cell.

Kurzfassung

In der letzten Dekade nahm der Einsatz mobile Datendienste in zellularen Netzen stark zu- und führte zu einem exponentiellen Anstieg der Nutzerdaten. Die aktuellen Technologien weisen jedoch, bezogen auf das geforderte Datenvolumen, Einschränkungen auf, die auch in den kommenden Jahren zu einem unzureichenden Durchsatz führen werden.

Die Erhöhung des Durchsatzes für Nutzerdaten erfordert die Suche nach einem effizienten Ansatz um das steigende Datenvolumen zu bewältigen. Ein möglicher Ansatz ist Device-to-Device (D2D) Kommunikation als ein unkonventionelles, mobiles Paradigma, das hohen Datenverkehr skalierbar auf lokale Peer-to -Peer- Anwender überträgt. Dabei werden die Ressourcen zwischen D2D- und zellularen Nutzern aufgeteilt, wobei der D2D-Datenverkehr direkt zwischen Endgeräten, d.h. ohne Einsatz der Basis Station erfolgt. Dadurch kann das Frequenzspektrum effizienter genutzt, und somit der Gesamtdurchsatz der Zelle erhöht werden. Zugleich wirken sich mehrere Faktoren negativ auf den Durchsatz der D2D-Kommunikation im zellularen Spektralband aus, wie z. B. die Interferenz zellularer Endgeräte, die weiterhin direkt mit der Basisstation kommunizieren. Zusätzlich reduziert geringe Aktivität der zellularen Endgeräte über die zugewiesenen Ressourcen die Spektraleffizienz, mit negativer Auswirkung auf den Durchsatz der D2D-Verbinding. Das kann dazu führen, dass die gewünschte Qualität des Datendiensts nicht erreicht wird.

Die Lösung der oben genannten Probleme erfordert: i) die Entwicklung entsprechender Zugriffsmechanismen für die D2D-Kommunikation, um die gewünschte Qualität der Service-Anforderungen mobiler Datendienst zu erreichen; ii) die Auslastung des Funkspektrums des lizenzierten Bands zu erhöhen, indem nicht lizenzierten Nutzern temporär freie Bereiche des Spektrums verwenden; und iii) die Entwicklung eines Prozesses zur Link-Adaption unter Berücksichtigung des dynamischen Verhaltens des zellularen Systems, so dass sich der Durchsatz der D2D-Verbindung erhöht . Die vorliegende Arbeit stellt die oben genannten Lösungen für die D2D-Kommunikation, die den Gesamtdurchsatz in der Zelle erhöhen sollen, vor. Die Hauptbeiträge sind: i) ein positionsbasierter, hybrider Zugriffsmechanismus für die D2D-Kommunikation; ii) ein hybrider Zugriffsmechanismus für unlizenzierte Peer-to-Peer Nutzer (unlizenzierte D2D-Kommunikation); und iii) ein Algorithmus zur Link-Adaption der unlizenzierten D2D-Kommunikation.

Zuerst wird in dieser Arbeit ein positions-basiertes Modell entwickelt, um den Durchsatz der D2D-Kommunikation zu maximieren, wobei unterschiedliche Zugriffsmechanismen eingesetzt werden. Im Modell werden die Regionen in der Zelle definiert, in der die D2D-Kommunikation mit der gewünschten Service-Qualität (QoS) durchgeführt werden kann. Anschließend wird ein positionsbasierter, hybrider Zugriffsmechanismus vorgestellt, der beim Einsatz für ein D2D-Paar zur Erhöhung des Gesamtumsatzes der Zelle führt. Die vorgeschlagenen Zugriffsmechanismen werden durch numerische Simulationen evaluiert. Die Ergebnisse zeigen Verbesserungen im Gesamtdurchsatz und der Anzahl der zufriedenen D2D-Kommunikationen in der Zelle.

Als nächster Schritt wird kognitive Funktechnik (Cognitive Radio) in das unlizenzierte D2D-Paar integriert, wodurch ein dynamischer Zugriff auf das Funkspektrum erreicht wird. Die neu eingeführten Zugriffsmechanismen und der jeweilig erreichbare Durchsatz werden untersucht. Als Ergebnis wird ein positionsbasierter, hybrider Zugriffsmechanismus eingeführt, um die Regionen mit unlizenzierter D2D-Kommunikation zu vergrößern. Zur Evaluierung des vorgeschlagenen Zugriffsmechanismus werden numerische Simulationen eingesetzt. Die erzielten Ergebnisse weisen Verbesserungen im Durchsatz, sowohl innerhalb der Zelle, als auch in der unlizenzierten D2D-Kommunikation, nach.

Als letzter Schritt wird das dynamische Verhalten der zellularen Umgebung, sowie ihrer Interaktion mit der unlizenzierten D2D-Kommunikation untersucht. Als eine mögliche Lösung wird der Einsatz künstlicher Intelligenz als eine kognitive Maschine vorgestellt, um die Funkverbindung effizient zu adaptieren. Auf Basis der Studie wird der Algorithmus „Self-Organized Link Adaptation" (SOLinA) vorgestellt, um die Funkverbindung der unlizenzierten D2D-Kommunikation autonom anzupassen und die VerbindungsKonfiguration so anzupassen, dass der Systemdurchsatz erhöht wird. Evaluiert wird der vorgeschlagene Algorithmus durch Simulationen der unlizenzierten D2D-Kommumikation innerhalb einer dynamischen zellularen Umgebung. Die neuesten Simulationsergebnisse zeigen, dass SOLinA die zuvor erzielten Ergebnisse beim Durchsatz, sowohl für unterschiedliche Konstellationen der unlizenzierten D2D-Kommunikation, als auch für unterschiedliche Anforderungen an das zellulare System und für variierende Positionen der Nutzer in der Zelle übertrifft.

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1 Introduction

Contents

The number of mobile data devices have been dramatically increased in the last few years. Many of these devices increase the monthly usage of the data services offered by cellular technologies. Such an increment in the usage of data services leads to an explosive growth in user's booming data demands during the next few years. However, the current allocated resources are limited in the 4G technologies, which makes the former lack of the user's data demands in the next 7 years. This limitation rises the problem of inefficient throughput within the current cellular technologies, as shown in Fig. 1.1 [Cla14].

To cope with the growth of mobile data demands, three approaches can be applied to the current cellular technologies: i) increasing the cellular resources, ii) increasing the density of the Base Stations (BS), and iii) seeking for new paradigms to improve the spectrum utilization. However, increasing the spectrum resources is an expensive approach because it requires buying more licensed spectrum bands, and because it provides

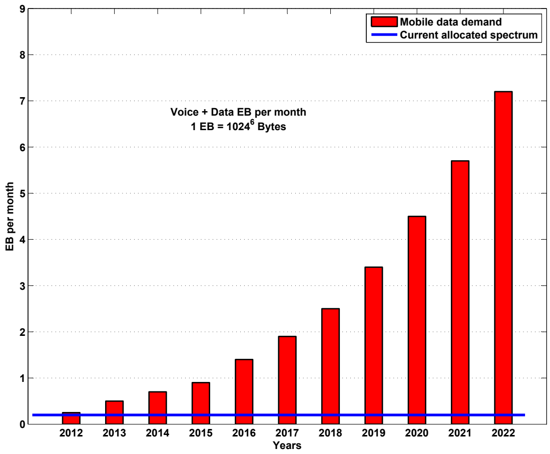

Figure 1.1: Forcasted growth of mobile data traffic 2012-2022 and the current allocated spectrum [Cla14]

limited improvement in throughput due to practical conditions. Also, increasing the density of BSs is also an expensive approach to implement, especially because it requires a high speed back-haul to connect large number of BSs [JCM13]. The drawbacks of the aforementioned approaches push the researchers to search for unconventional paradigms to the spectrum allocation process.

One of the proposed solutions is to apply mobile data offloading techniques through other technologies (such as WiFi and Bluetooth). The goal of mobile data offloading is to reduce both the mobile data traffic in the cellular band and the battery energy consumption at the User Equipment (UE) [LLY+10]. However, such technologies still have some challenges such as uncontrollable interference, a lack of security and the Quality of Service (QoS) requirement may not be met [AWM14, TUY14]. These drawbacks have pushed the researchers to think of implementing data offloading in cellular band due to their interference management scheme, which has resolved many existing challenges. However, such bands need an unconventional paradigm to cap the growth of data traffic. [JKR+09] claims a reliable paradigm to handle local peer-to-peer mobile data traffic within scalable manner. This paradigm is called Device-to-Device (D2D) communication.

The D2D communication is applicable between two close UEs without traversing the BSs. Thus, the cellular resources can be shared between conventional cellular UEs (UE_Cs) and the D2D-based UEs (UE_Ds). Integrating D2D communication within cellular networks can increase the spectrum utilization which improves the total throughput in the cell, especially with high data rate services such as video sharing and gaming.

In addition, it reduces the energy consumption at UE_D [CDY+12, JHC12, LZLS12, FLYW+13, SJWL13, KLA13, TUY14, AWM14].

However, D2D communication still suffers from some issues that cause negative impact on the throughput of the system. One of the main issues is the interference from the cellular entities (BS or UE_Cs) to the UE_Ds which causes a degradation of the Signal to Interference plus Noise Ratio (SINR) at UE_Ds by using underlay access paradigm which limits the upper transmit power of the UE_D. Also, the low spectral efficiency, using overlay access paradigm, is still an issue due the division of the resources orthogonally between the UE_Cs and UE_Ds which reduces the bandwidth for the both cellular and the D2D communication.

Another issue is the spectrum assigned to the licensed systems which are in use infrequently due to the low activity of these systems per time. This manner causes many white spaces (spectrum holes) in the spectrum band which makes a negative impacts on spectrum utilization, especially in high traffic load areas (urban areas) [DPS13]. The available limited spectrum and the inefficient spectrum utilization necessitate a new communication paradigm to exploit the existing cellular spectrum opportunistically [AAFS04]. On the other hand, the unlicensed users faces many problems while using the crowded unlicensed spectrum band, such as interference. One proposed solution is the Dynamic Spectrum Access (DSA) strategy used by UE_Ds which are equipped with a smart radio called Cognitive Radio (CR) to share the cellular spectrum resources in an opportunistic manner. The CR is defined as the intersection of personal wireless technology and computational intelligence. It is self-aware, radio frequency-aware, and user-aware with a lot of high-fidelity knowledge of the radio environment [III00].

According to [HBN+10], a CR uses an intelligent entity called the Cognitive Engine (CE) which is the core of the CR. The CE manages the performance of the CR autonomously in a dynamic radio environment by: i) monitoring and understanding the behavior of the radio environment and the radio's capability (spectrum-awareness and self-awareness); ii) deciding the best action (which resource block and which configuration of radio parameters) to apply in order to meet the QoS requirements; iii) learning the influences of the decided actions on the behavior of radio environment (spectrum band), as well as the performance of CR [CHSO07, HBN+10, APB+10]. The researchers in [CDY+12, SH14] proposed integrating CR technique within the UE_Ds to perform unlicensed D2D (UD2D) communication so as to improve the spectrum utilization and the energy saving in the cellular network. However, some issues are still open such as: i) interference at UE_Ds is still uncontrollable due to the priority of cellular network, ii) the inter-dependency between different link objectives for each user application (such as throughput, energy saving, delay, etc.) makes the configuration of UD2D link as a Multi-Objective Optimization Problem (MOOP), and iii) dynamic behavior of cellular network pushes $\mathrm{UE_D}$s to adapt UD2D link frequently which leads to an increase in energy consumption and computational overhead, as well as a decrease in system throughput.

The goal of this dissertation is to improve the throughput of the cellular system and the spectrum utilization within the challenges of data booming demands and the dynamic behavior of the cellular network. Thus, the focus of this dissertation is on applying D2D communication and UD2D communication to improve the performance of future cellular systems. The dissertation presents a model for estimating the system spectral efficiency in term of geographical positions of cellular entities. Then it presents a hybrid access paradigm for D2D communication to improve the system spectral efficiency. Then, it presents a new paradigm for spectrum access to improve the performance of the system spectral efficiency over the cell using UD2D communication. Later, the dissertation presents a self-organizing algorithm to improve the link performance of UD2D communication. The proposed algorithm applies a heuristic-based search technique to optimize the UD2D communication link so as to meet the desired QoS requirements, as well as to avoid interference with $\mathrm{UE_C}$s. To speed up the convergence, an expert system technique has been included to exploit the predefined actions under similar environmental observations. Also, learning technique has been included to learn the impacts of the proposed actions on the radio environment. The proposed algorithm has been evaluated throughout simulation scenario of a cellular communication system. The results show improvements in the goodput, compared to the literature.

1.1 Motivations

Although integrating D2D and UD2D communication within the cellular system have offered an improvement in the spectrum utilization and system spectral efficiency, several issues rise which have negative impacts on the performance of the cellular network, as well as D2D and UD2D communication.

1.1.1 Intra-Cell Interference

First, while $\mathrm{UE_D}$ pairs communicate using a cellular spectrum band, they may generate an interference to cellular entities. The generated interference by the $\mathrm{UE_D}$ transmitter ($\mathrm{UE_D}$-Tx) becomes harmful to the cellular receiver (BS in uplink band and $\mathrm{UE_C}$ in downlink band). The intra-cell interference, caused by D2D communication, pushes

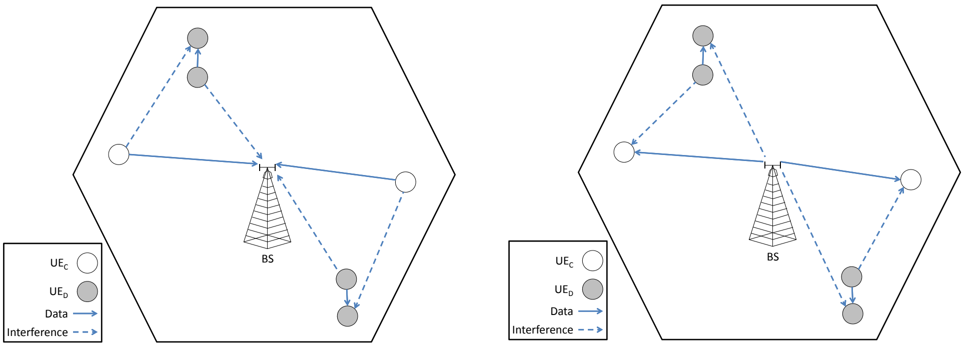

Figure 1.2: Interference between UE_Ds and cellular system in (a) uplink and (b) downlink scenarios

cellular entities to increase their transmit power, which will increase the interference with the UE_D receiver (UE_D-Rx). Generating interference on both sides (UE_D pairs and cellular system) during communication may make them unable to meet their QoS requirements. Figure 1.2 shows cellular network that uses Frequency Division Duplex (FDD) system and UE_Ds pair in uplink (UL) and downlink (DL) bands. In UL band, UE_D-Tx generates interference at BS, while UE_Cs generate interference at UE_D-Rx, as shown in Fig. 1.2 (a). In DL band, UE_D-Tx generates interference at UE_C, while the BS generates interference at UE_D-Rx, as shown in Fig. 1.2 (b). Researchers in [DYRJ10, XTL11, LZLS12, JHC12, FLYW$^+$13] proposed D2D communication using underlay access paradigm with a full control of BS to resource allocation and power control of UE_Cs and UE_D pairs. However, interference generated by BS (in DL) or UE_C (in UL) to UE_D-Rx is still an issue which degrades the SINR of D2D communication link and reduces the system spectral efficiency.

1.1.2 Low Spectrum Utilization

Second, although the BS allocates spectrum to UE_Cs while they are in the coverage area of the BS (inside the cell), the UE_C's activities vary over time according to the user application demands. Some applications have low activity (which may use 15% of the assigned resources) according to the user application [ALVM06]. Such low activities of UE_C increase the number of spectrum holes in the spectrum band, which degrades the spectrum utilization. In LTE-Advanced systems, a dynamic resource allocation scheme has been used to increase the spectrum utilization in the cell. However, the LTE spectrum still has many spectrum holes which can be utilized to improve the spectrum utilization [CCYC11].

1.1.3 Interdependency between Link Objectives

Third, sharing a spectrum band requires re-configuring the radio parameters (such as transmit power, modulation scheme, frame length, carrier frequency, etc.) to optimize the performance of UD2D communication, as well as to avoid interference with the cellular systems. However, these radio parameters have impacts on different link objectives (such as throughput, energy saving, etc.) which make interdependency between the link objectives and influence the performance of the UD2D communication. The previous studies have proposed many algorithms (such as heuristic-based algorithms) to optimize such a problem [Rie04, ZXZS09, CNEW10, ZLW12]. However, many drawbacks have appeared, such as slow convergence, low fitness value and inability to move from local optima regions. These drawbacks have negative influences on the throughput of the system.

1.1.4 Stochastic Radio Environment

Fourth, the stochastic behavior of the cellular radio environment crucially affects the stability of UD2D communication link and may have a negative impact on the QoS. Thus, the UE_{D}s must frequently reconfigure their links within any change in the cellular radio environment. By performing the reconfiguration frequently, the throughput of the system will have a degradation due to the increment of: i) the signaling overhead, ii) the spectrum hand-off, and iii) the computational overhead. Some researchers proposed expert system techniques in order to reduce the computational overhead [CHSO07, HBN+10], while other researchers proposed algorithms to learn the best configuration of radio parameters to reduce the spectrum hand-off [LDCV12, Hus10]. However, these algorithms have many drawbacks, such as high computational efforts, slow convergence, more memory for unstable environments, and the possibility of over-training [JGL08, HBN+10].

1.2 Goals

The goal of this dissertation is to solve the aforementioned open issues, by:

- Studying the behavior of the system spectral efficiency according to the geographical positions of all the entities in the cell, as well as their QoS requirements in D2D and UD2D communications.

- Improving the system spectral efficiency and the spectrum utilization of the cellular systems.

- Increasing the number of satisfied users in the cell (through D2D and UD2D communication)
- Achieving an autonomous link adaptation algorithm at UE_D to avoid interference from cellular entities in underlay mode.
- Studying the influence of geographical positions of cellular entities on the behavior of goodput of UD2D communication.

1.3 Contributions of the Dissertation

This dissertation provides three contributions to the field of communication in cellular system. The first contribution proposes a hybrid access paradigm for D2D communication which optimizes the system spectral efficiency. The second contribution is proposing a new access paradigm for integrating UD2D communication with the cellular system to improve the spectral efficiency of the system. The third contribution presents a heuristic-based algorithm to perform link adaptation of UD2D communication under dynamic radio environment.

1.3.1 Analytical Model of System Spectral Efficiency for D2D Communication

Several previous works have focused on the data offloading using D2D communication using cellular resources. These studies proposed different schemes to optimize performance of the conventional cellular communication and D2D communication to improve the spectral efficiency and optimize the energy consumption of the UEs. However, D2D communication still has some drawbacks such as interference from the cellular entities which has a negative influence on the performance of D2D communication at different positions in the cell, especially at positions close to cellular entities (BS and UE_Cs) which prevent preforming D2D communication. Some limited studies discussed the effect of geographical position of a UE_D pair on its performance, but they did not study the influence of geographical positions of the cellular entities. Also, their study did not solve the problem of interference on UE_Ds at positions close to cellular transmitters.

The first contribution of this dissertation is modeling the system spectral efficiency in the cell depending on the geographical positions of the UE_D pairs and UE_Cs in the cell using the recent access paradigms. The proposed model is based on previous limited studies which discussed the influence of geographical position of UE_D pair on its performance in underlay access paradigm. Then, a hybrid access paradigm is proposed which optimizes the system spectral efficiency by selecting the proper paradigm for each individual UE_D pair according to the positions of UE_Cs and UE_D pairs in the cell. The proposed access paradigm is called Underlay-Overlay (UnOv) access paradigm. The simulation of D2D communications using the proposed access paradigm show improvements in system spectral efficiency over the cell, as well as increase in the area used by UE_D pairs.

1.3.2 Analytical Model of System Spectral Efficiency for Unlicensed D2D (UD2D) Communication

Improving the spectrum utilization and spectral efficiency are the main goals from integrating D2D communication within cellular system. However, the low activities of UE_Cs over time and space makes some spectrum holes over the spectrum band. Many different techniques have been proposed to invest these holes such as dynamic allocation scheme in LTE-Advance systems. However, the spectrum holes are still available over time-space-frequency [CCYC11]. Some researchers proposed the usage of CR technique to invest these spectrum holes by the unlicensed users (UD2D communication) in order to improve the spectrum utilization and spectral efficiency [CDY+12, SH14]. However, there are some drawbacks which limit the performance of CR technique such as the intra-cell interference from the cellular users to the UD2D communication, the degradation of cellular SINR due to the miss-detection of cellular activities and common spectrum holes on both sides of UE_D pair.

The second contribution of this dissertation is studying the system spectral efficiency in presence of UD2D communication depending on the position of UE_D pair in the cell. The spectral efficiency is modeled for different access paradigms (using CR techniques) to study the impact of geographical positions and QoS requirements on the system spectral efficiency. Then, a hybrid access paradigm is proposed which merges the underlay paradigm (in D2D communication) and interweave paradigms (in CR technique) to utilize the resources at different positions in the cell. The proposed paradigm focuses on accessing the resources at close positions to the UE_Cs when they are in OFF periods (using interweave), while accessing the resources in parrele with the cellular system at the cell edge. The proposed paradigm shows improvements in the achievable spectral efficiency of UD2D communication, the system spectral efficiency and the area used in the cell to perform UD2D communication.

1.3.3 Self-Organized Link Adaptation (SOLinA) Algorithm for UD2D Communication

Several different algorithms have been implemented to achieve fast link adaptation process in CR under dynamic radio environment. Some of these algorithms are based on merging different techniques to include more features in the operation of the CE. However, several of the proposed algorithms have some issues which are still open, such as high convergence time, excluding frequency from optimized radio parameters, high computational efforts and signalling overhead, as well as they did not study a realistic scenario of cellular network [NRW$^+$07, ZGM$^+$07, NH09, Red10, dBMP08].

The third contribution of this dissertation is presenting heuristic-based algorithm which optimizes UD2D communication link under dynamic radio environment. The proposed algorithm adds self-organization feature to the UD2D communication to perform fast and autonomous link adaptation process without interfering the cellular networks. The proposed algorithm is called Self-Organizing Link Adaptation (SOLinA) algorithm which merges optimization, reasoning, and learning techniques. To evaluate the proposed algorithm, different scenarios of dynamic radio environment in cellular system in UL (e.g. dynamic $\mathrm{UE_C}$ activity, noise floor, interference, path loss, SINR, etc.) has been simulated. The results show several improvements in goodput of UD2D communication under different spacing between the $\mathrm{UE_D}$ pair, different cellular QoS requirements and at different positions in the cell, compared to the literature.

Different parts of this work have been published in [MMKMT12, MKMT13a, MKMT13b, MAM$^+$14]:

[MMKMT12] *A. Mahdi, J. Mohanan, M. Kalil, A. Mitschele-Thiel, "Adaptive Discrete Particle Swarm Optimization for Cognitive Radios", in Proc. IEEE International Conference on Communications (ICC), Ottawa, Canada, June 2012, pp. 6550-6554*

[MKMT13a] *A. Mahdi, M. Kalil, A. Mitschele-Thiel, "Cross Layer Optimization for Efficient Spectrum Utilization in Cognitive Radios", in Proc. International Conference on Computing, Networking and Communications (ICNC), San Diego, USA, January 2013, pp. 305-309*

[MKMT13b] *A. Mahdi, M. Kalil, A. Mitschele-Thiel, "Dynamic Packet Length Control for Cognitive Radio Networks", in Proc. IEEE 78th Vehicular Technology Conference (VTC2013-Fall), Las Vegas, USA, September 2013, pp. 1-5*

[MAM+14] *A. Mahdi, Z. Ansar, S. Mwanje, O. Artemenko, A. Mitschele-Thiel, "Q-CE: Self-Organized Cognitive Engine based on Q-Learning", in Proc. IEEE Wireless Communications and Networking Conference (WCNC), Istanbul, Turkey, April 2014, pp. 202-207*

1.4 Outline of the Dissertation

This dissertation focuses on studying the integration of D2D communication with future cellular networks using different access paradigms.

In Chapter 2, the principles of D2D communication are introduced, and the modes of operation are explained in details. Then, the CR technique is presented, and the role of CE in improving the performance of CR nodes is explained in details. Later, the literature survey of existing work in D2D communication is presented. Then, a conclusion about the current open issues is given.

In Chapter 3, a brief introduction about the system model of cellular system and D2D communication. A geographical-based model of system spectral efficiency is presented for underlay and overlay access paradigms. Then, the proposed access paradigm is explained in details and its model of spectral efficiency is derived. Later, numerical simulations have been performed to evaluate the performance of the proposed access paradigm, compared to other paradigms.

In Chapter 4, a description of system model for UD2D communication is introduced. A geographical-based model of spectral efficiency using CR technique in UD2D communication within different access paradigms is presented. Then, a hybrid access paradigm for UD2D communication is proposed with its model of the system spectral efficiency based on the geographical positions and the user activities. Later, numerical simulations have been performed to evaluate the performance of the proposed access paradigm, compared to other paradigm.

In Chapter 5, the problem of link adaptation under dynamic radio environment is explained in details. The literature survey of link adaptation algorithm is introduced. Then, a new self-organizing algorithm is proposed to perform as CE for UD2D communication with cellular systems. The architecture and the operational procedure of proposed algorithm are explained in details.

In Chapter 6, a simulation scenario has been presented to evaluate the performance of SOLinA algorithm for UD2D communication. The simulation assumptions have been presented, as well as different models related to interference, propagation and cellular activities. Later, the outcomes of applying the SOLinA algorithm are shown in an analysis of its performance.

In Chapter 7, the contributions of the dissertation to D2D and UD2D communication fields are summarized, and the conclusion is explained. Also, suggestions for future work are presented.

2 Background and Literature Survey

Contents

In this chapter, the background of D2D communication is presented, and the modes of operations are described in details with their relation to the access paradigms. Then, weaknesses in the D2D communication are discussed. The role of CR technique to improve the D2D communication is explained. Then, a background on CR technique is presented, and its architecture is explained in detail. The role of the CE in improving the performance of CR is explained in detail. Later, the literature survey of existing work in D2D communication is presented. Also, the strengths and weaknesses in the literature are analyzed. Finally, a discussion of open issues in D2D communication that have not yet been solved is presented.

2.1 D2D Communication Background

The exponential growth of mobile data traffic is one big challenge for the mobile operators who use highly efficient cellular networks (4G) to fulfill the demands of booming

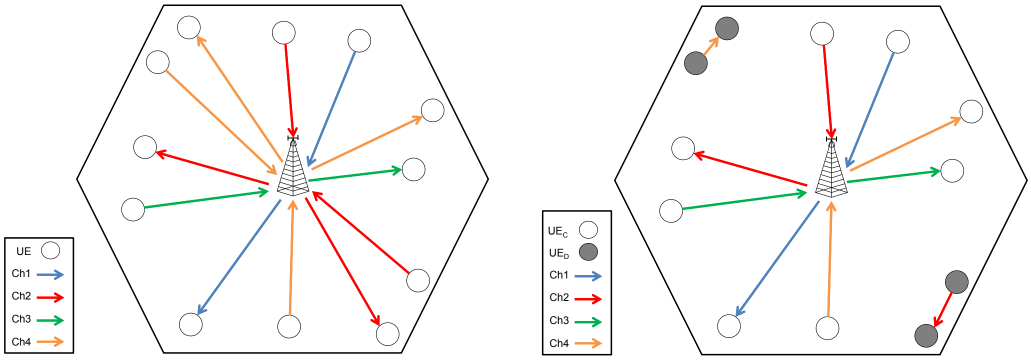

Figure 2.1: System model in one cell of (a) conventional cellular system; (b) D2D communication integrated with cellular system

data traffic. Growing demands of the mobile data traffic in the future will require unconventional next generation cellular systems. One of the proposed solutions is to apply mobile traffic offloading through direct communication between close UEs using the cellular spectrum band with a limited involvement (control) of BS to achieve a better spacial diversity [TUY14], as shown in Fig. 2.1. By allowing direct D2D communication between relatively close UEs, many improvements can be achieved in terms of system throughput, energy savings, network resource utilization, end-to-end latency, network capacity, and robustness to infrastructure failures [YSCA13].

In each cell in the cellular networks, each UE has its own Channel State Information (CSI) that represents the channel property of a communication link. The UEs send their CSI's to the BS in the cell so as to have a full CSI over the cell. The BS uses the full CSI to allocate the available resources to the UEs in the cell. Some UEs may be far from the BS, close to each other, and request to exchange data with high data rates. Such UEs may have unreliable communication within the conventional cellular network due to the distance from the BS which requires a transmit power above the boundary. In such a case, applying D2D communication becomes a better decision and achieves energy saving and traffic offloading.

2.2 Operation Modes of D2D Communication

To achieve the aforementioned improvements in the system performance, the BS allocates some cellular resources to UE$_D$s in order to perform D2D communication [YTDR09, YDRT11, XTL11]. According to the geographical positions of UE$_D$ and the resource allocation scheme, the UE$_D$s have to operate in three different modes [YTDR09, DYRJ10,

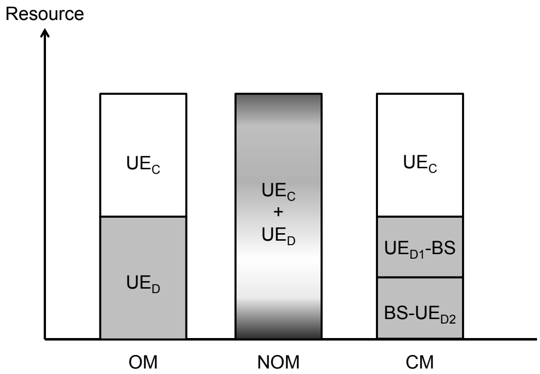

Figure 2.2: Operation modes in D2D communication [YTDR09]

TUY14, AWM14], which are illustrated in Fig. 2.2:

- **Orthogonal Mode (OM)**: The BS allocates dedicated portions of the resource to $\mathrm{UE_C}$ and $\mathrm{UE_D}$ pair in such a way that there are no interference between $\mathrm{UE_D}$s and $\mathrm{UE_C}$s. Thus, $\mathrm{UE_D}$ pairs send the data with the maximum transmit power to achieve the highest possible data rate and maximum spectral efficiency. The SINR of cellular system $\Gamma_{C_{OM}}$ is defined as:

$$\Gamma_{C_{OM}} = \frac{P_C d_C^{-\gamma}}{\sigma_n^2}, \tag{2.1}$$

where P_C is the transmit power of cellular transmitter (C-Tx), σ_n^2 is the noise power, d_C^{γ} is the path loss in cellular link, and γ is the path loss exponent (γ=2,...,4.5 according to the type of the communication link) .

While the SINR of the D2D communication $\Gamma_{D_{OM}}$ is defined as:

$$\Gamma_{D_{OM}} = \frac{P_D d_D^{-\gamma}}{\sigma_n^2}, \tag{2.2}$$

where P_D is the transmit power of $\mathrm{UE_D}$ transmitter ($\mathrm{UE_D}$-Tx) and d_D^{γ} is the path loss in D2D link.

- **Non-Orthogonal Mode (NOM)**: The $\mathrm{UE_D}$ pairs share the same resources with the $\mathrm{UE_C}$s. In this mode, the spectrum utilization is improved due to re-utilizing the whole resource simultaneously ($\mathrm{UE_C}$s and $\mathrm{UE_D}$s). The SINR of the cellular system $\Gamma_{C_{NOM}}$ is defined as:

$$\Gamma_{C_{NOM}} = \frac{P_C d_C^{-\gamma}}{IF P_D d_{DC}^{-\gamma} + \sigma_n^2}, \tag{2.3}$$

where IF is the interference factor $IF \in \{0, 1\}$, $d_{DC}^{-\gamma}$ is the path loss between the UE_D-Tx and the cellular receiver (C-Rx). While the SINR of the D2D communication $\Gamma_{D_{NOM}}$ is defined as:

$$\Gamma_{D_{NOM}} = \frac{P_D d_D^{-\gamma}}{IF P_C d_{CD}^{-\gamma} + \sigma_n^2}, \tag{2.4}$$

where $d_{CD}^{-\gamma}$ is the path loss between C-Tx and UE_D receiver (UE_D-Rx).

The $\Gamma_{C_{NOM}}$ and $\Gamma_{D_{NOM}}$ have a noticeable degradation compared to $\Gamma_{C_{OM}}$ and $\Gamma_{D_{OM}}$ due to the interference from UE_D-Tx ($P_D d_{DC}^{-\gamma}$) and from C-Txs ($P_C d_{CD}^{-\gamma}$) respectively. However, the whole resource is allocated to both UE_C and UE_D pairs, compared to OM.

- **Cellular Mode (CM)**: The UE_D pairs communicate through the BS which acts as a relay when the distance between the UE_Ds requires a high transmit power which causes an interference to the other UE_Cs. This mode is conceptually similar to the conventional cellular communication. The BS allocates portion of the resource to UE_D pair which is divided into two portions for UL and DL. The SINR at UE_D-Rx in this mode $\Gamma_{D_{CM}}$ is defined as [YTDR09]:

$$\Gamma_{D_{CM}} = \frac{P_B d_{BD}^{-\gamma}}{\sigma_n^2} \tag{2.5}$$

where P_B are the transmit power of the BS and $d_{BD}^{-\gamma}$ is the path loss between the BS and UE_D-Rx.

Researchers have classified the OM and CM as applicable modes using an access paradigm called Overlay (Ov), which assigns dedicated portion of the resources to D2D communication with the usage of maximum transmit power and the absence of interference. However, using Ov paradigm leads to low spectral efficiency due to no re-utilization of resources in positions which have no interference from other entities in the cell, as well as the partial usage of the resources by the UE_D pairs and UE_Cs. Figure 2.3 (a) and (b) show the usage of Ov access paradigm in OM and CM.

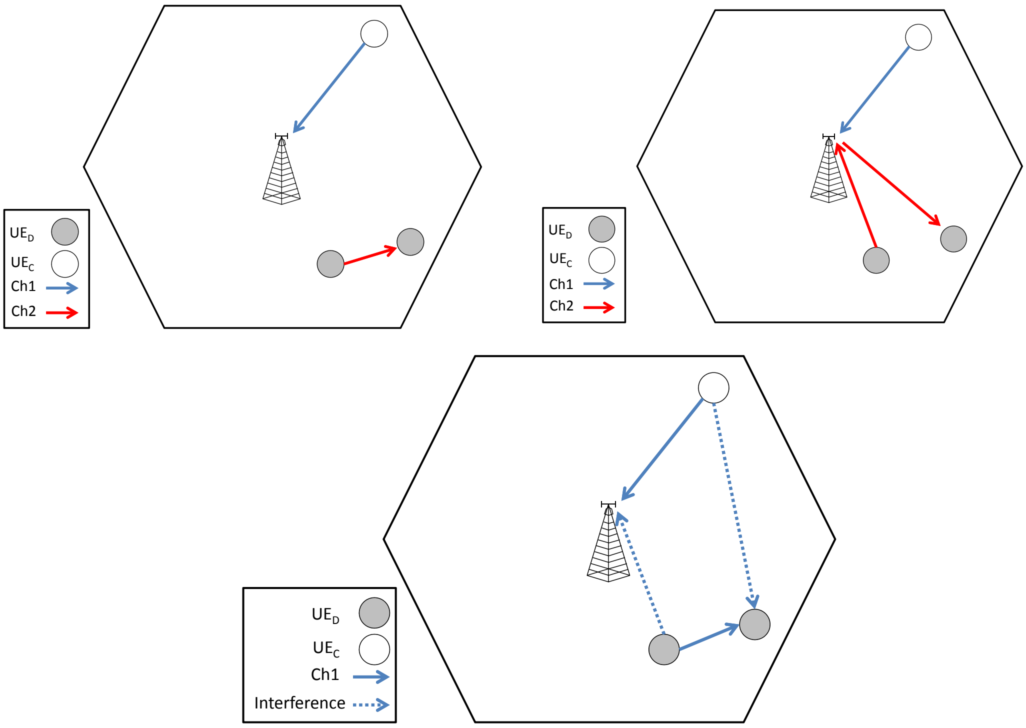

Figure 2.3: Access paradigm for (a) OM; (b) CM; and (c) NOM

To improve both of spectrum utilization and spectral efficiency in the cellular system, NOM can be used to share the whole resources of the cellular system between both of $\mathrm{UE_C}$ and $\mathrm{UE_D}$ pairs simultaneously. However, the main challenge in this mode is the mutual interference between the cellular and D2D communications which reduces $\Gamma_{C_{NOM}}$ and $\Gamma_{D_{NOM}}$. To cap the mutual interference challenge, researchers proposed different resource allocation and power control schemes to avoid interference at cellular entities as the main goal, and to improve the data rate of D2D communication as a secondary goal. Such schemes are classified as an underlay (Un) access paradigm which focuses on limiting the transmit power of $\mathrm{UE_D}$ pairs to generate a tolerable interference at the cellular network. Thus, the BS sets higher priority in the resource allocation scheme for the $\mathrm{UE_C}$s than the $\mathrm{UE_D}$s by defining a higher threshold for $\Gamma_{C_{NOM}}$ than for $\Gamma_{D_{NOM}}$ [JKR$^+$09, DYRJ10, KLA13]. Figure 2.3 (c) shows the usage of Un access paradigm in NOM.

2.3 Weaknesses in D2D Communication

Although applying D2D communication has improved the spectral efficiency of the system, it has some weaknesses which make negative impacts on the performance of the system in general.

By using Ov paradigm in OM and CM, the system has to allocate orthogonally a portion of the resources for D2D communication to perform such modes without interfering the cellular communication. Such a case leads to reduce the spectral efficiency of both the $\mathrm{UE_C}$s and the system, as well as increase the number of unsatisfied $\mathrm{UE_C}$s in high data traffic-based scenarios (urban area) [AJM14].

By using Un paradigm to avoid interference at the cellular network in NOM of operation, the degradation of $\Gamma_{D_{NOM}}$ at the $\mathrm{UE_D}$s is still an issue due to its low threshold value which reduces the achieved data rate. Such a paradigm puts the $\mathrm{UE_D}$s out of service in crowded cells in which the resources are mostly allocated to the close $\mathrm{UE_C}$s. Also, sharing the resources does not guarantee simultaneous transmissions of cellular and D2D communication due to the priority of cellular communication, which leads to have two kinds of regions in the cell: i) D2D and cellular communication regions which has high system spectral efficiency; and ii) cellular communication regions, which has relatively low spectral efficiency. All the operation modes of D2D communication require a coordination from the BS for assigning the resources so as to achieve a controlled interference environment [AJM14].

In addition to the issues in D2D communication, assigning resources to $\mathrm{UE_C}$s with low activity (such as 15%) leads to high number of spectrum holes which represents idle periods of $\mathrm{UE_C}$s. A high number of such periods over the dedicated resources will degrade the spectrum utilization of the system, especially in crowded cells in which some $\mathrm{UE_D}$s wait for some free resources to use.

To improve the spectrum utilization, CR is a promising technology to perform DSA strategy in the cellular spectrum resources. J. Mitola defines CR as an intelligent point that can detect user communications needs, and can provide the most appropriate radio resources for these needs [MM99].

2.4 Cognitive Radio Background

Cognitive Radio (CR) is built on Software Defined Radio (SDR) technology to achieve autonomous rapid reconfiguration of radio parameters. By reconfiguring its radio parameters, CR can ensure a communication between the unlicensed users, i.e. Secondary

Users (SUs) which meet QoS requirements without interference with cellular entities, i.e. Primary Users (PUs) [RB09].

The ability of CR to achieve this goal depends upon the following attributes [HBN+10]:

- **Observation**: To collect data about the surrounding radio environment (such as channel conditions, neighbor cellular entities and their activities), user requirements (such as latency and throughput), and radio capability (such as radio parameters capability, battery power, and available computational resources).
- **Cognition**: To understand the radio environment, to determine the proper actions to apply, and to learn the impacts of different actions on the performance of the radio, as well as on the performance of the network.
- **Reconfiguration**: To adapt the radio parameters according to the proposed actions.

In order not to interfere with PUs while using the licensed spectrum, CR uses certain access paradigms [GJMS09, BGG+12] to perform interference-free SU communication:

1. Underlay (Un) access paradigm in CR is similar to underlay paradigm in D2D communication, in which the CR transmits data under the noise level at the PUs so as not to interfere with them. Performing this access paradigms requires to set the upper limit of CR transmit power which should not exceed the interference threshold at the PU receiver.
2. Interweave (Iw) is the use of spectrum band at a certain frequency-time-space in which the spectrum hole is available at both SU's communication parties. This paradigm requires performing sensing on both communication parties to define the common spectrum holes.

2.5 Cognitive Radio Architecture

Achieving the aforementioned attributes requires a specific architecture for CR which performs the interaction between the surrounding environment, radio platform, and user requirements as shown in fig. 2.4.

The architecture of CR consists of [Rie04, Fet09, RB09]:

- **Communication System**, which is represented by the protocol stack /Open Systems Interconnection (OSI). The communication system includes the SDR, MAC protocol, and other upper layers services.

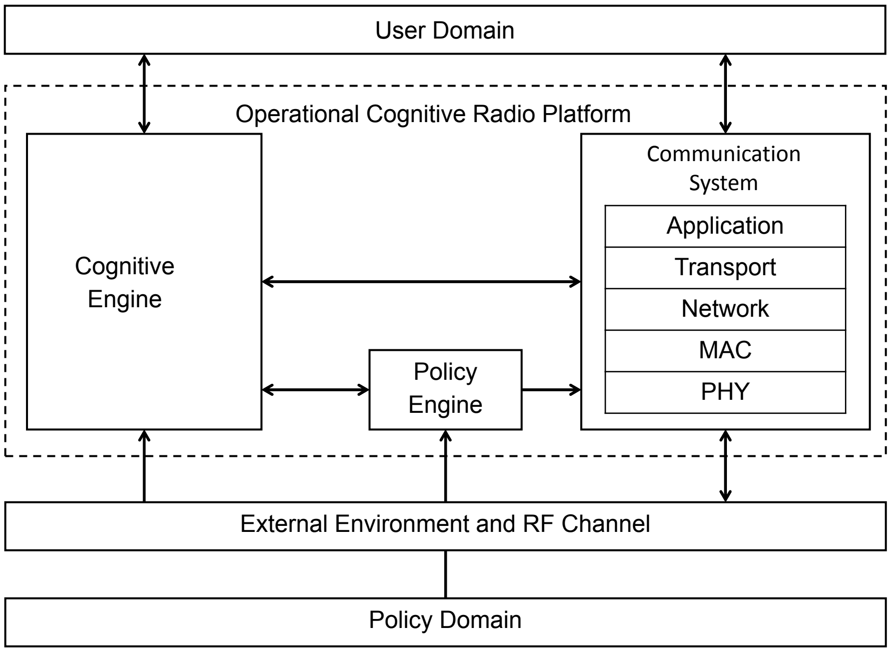

Figure 2.4: CR architecture [Fet09].

- **Cognitive Engine (CE)**, which is the intelligent core that performs modelling, learning, and optimization processes to alter the CR's behaviour according to the observations from the radio domain, and the application requirements from the user domain.

- **Policy Domain**, which is responsible for restricting the CR with boundaries and limitations, set by regulatory bodies. This information helps the CR to decide allowable (and legal) actions, and blocks any action that breaks regulations.

The radio domain supplies the CE with observations about RF such as signal strength and other environmental data that affects the communication system's performance. The user domain tells the CE about the service requirements that are related to QoS of the communication system [RB09].

2.6 Cognitive Engine

The CE is defined as the intelligent core in CR that performs the decision making and learning processes which alter the behavior of CR. To manage CR performance

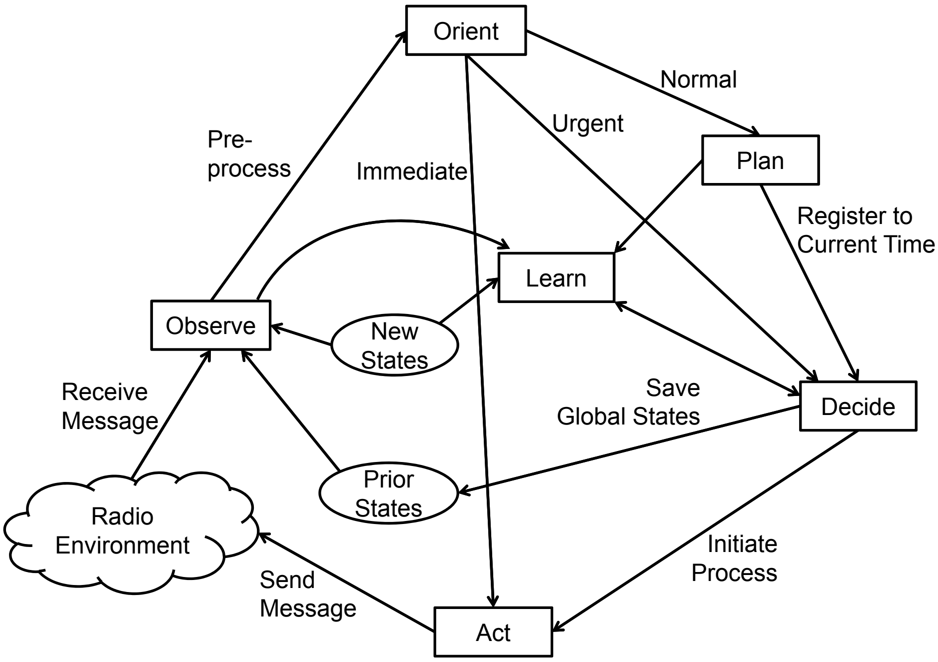

Figure 2.5: Cognition Cycle [III00].

autonomously during the communication process, the CE applies Artificial Intelligence (AI)-based algorithms by mixing traditional communication theory from electrical engineering while applying concepts from computer science [ALC09]. While a CE performs decision making and learning processes, it has the main role in the cognition cycle which the CR node must follow in its operation process, as shown in Fig. 2.5.

After observing the radio environment and defining the plans of the operations, the CE decides which useful actions are required to meet the QoS. An action is the configuration of radio parameters (such as the sub-channel frequency f_C, transmit power P, modulation scheme M, frame length L, etc.) which have influences on different services from different layers of protocol stack [New08]. Observations include: i) measurements of the surrounding radio environment such as Signal Strength SS; and ii) the performance of the transmission link between the SUs such as SINR, Bit Error Rate (BER) and data rate (R_b) [WNH09, Fet09]. Also, in the decision making process, the CR node should learn the influences (rewards) of the applied actions on the performance of the CR. The learning process assists the decision making process to determine the best action for improving the performance of the CR.

Because decision making and learning are the main processes in the cognition cycle, there is a need to find an efficient algorithm to perform these processes. The CE has been proposed as an intelligent core to perform these processes by implementing AI-based algorithms [WNH09, Fet09, RB09, NBW+07]. The implementation of AI-based algorithms for CEs achieves a radio system that can reconfigure itself autonomously according to the surrounding environment without any external interaction.

2.7 Literature Survey in D2D Communication

Recently, D2D communication became an interest for researchers who looked for traffic offloading from the cellular network in a local area. In this section, a survey of the previous studies on D2D communication in a cellular network is presented. In order to analyze the previous studies with their strengths and weaknesses, they have been classified into four classes according to their target for improvement: 1) spectral efficiency, 2) energy efficiency, 3) performance with QoS constraints, 4) reliability, and 5) spectrum utilization and fairness.

In the following subsections, each class of operation is described in detail, in addition to their weaknesses.

2.7.1 Spectral Efficiency

In [KA08, KLA13], the authors have considered D2D communication to be transparent to cellular network, and defined a spectrum sharing scheme between $\mathrm{UE_C}$s and Ad-Hoc D2D communication. The individual $\mathrm{UE_D}$s derive their transmit power in underlay paradigm and distribute it by route discovery packet to enable the establishment of a single-hop or multi-hop D2D communication.

The authors in [JKR+09] have investigated an interference-aware management scheme for D2D communication. The $\mathrm{UE_D}$s update the BS with the interference from $\mathrm{UE_C}$s, and the BS uses the channel gain between $\mathrm{UE_D}$s and $\mathrm{UE_C}$s to manage the resource allocation and the transmit power of both $\mathrm{UE_C}$s and $\mathrm{UE_D}$s.

In [DYRJ10, YDRT11], the authors have proposed operation mode algorithm for D2D communication. The BS has to select an operation mode and coordinates the transmit power of $\mathrm{UE_C}$s and $\mathrm{UE_D}$s to maximize the throughput of the system.

To manage the interference from cellular network to $\mathrm{UE_D}$s, the authors in [MLPH11] have introduced an interference management strategy. The proposed strategy prohibits $\mathrm{UE_C}$s, in the transmission range of $\mathrm{UE_D}$s, from using the same resources which are assigned to $\mathrm{UE_D}$s.

A two-stage semi-distributed resource management scheme for the D2D communication has been proposed in [LCJJ14]. The first stage includes allocation of the resource blocks by the BS to $\mathrm{UE_C}$s and $\mathrm{UE_D}$s. The second stage includes distributed operations: i) the BS schedules the usage of resource blocks, which are assigned to the $\mathrm{UE_C}$s; and ii) the $\mathrm{UE_D}$s adapt their link autonomously according to their assigned resource blocks.

2.7.2 Energy Efficiency

In [YTDR09, YDRT11], the authors have studied the power optimization problem of the shared radio resources. The BS assigns the radio resources and coordinates the power to $\mathrm{UE_C}$s and $\mathrm{UE_D}$s in order to optimize the throughput of the system.

Different power allocation algorithms have been proposed for D2D communication to improve the energy efficiency. The authors in [XTL11] have proposed a heuristic-based algorithm which performs resource allocation and mode selection to $\mathrm{UE_D}$s after allocating the resources to $\mathrm{UE_C}$s depending on the lower bound of P_D to meet the QoS constraints. While the authors in [JHC12] proposed an algorithm which selects the mode of operation that achieves higher power efficiency. However, such an algorithm must search all the possible modes of selection for each device.

2.7.3 Performance with QoS constraints

Many previous work have been applied using D2D communication to improve the performance of the cellular system and achieve the QoS constraints. In [ZHS10], a greedy heuristic-based resource allocation algorithm has been proposed within a fast scheduling period in LTE network. The authors formulated the resource allocation to $\mathrm{UE_D}$s into a mixed integer nonlinear problem with the priority of meeting the QoS requirements at $\mathrm{UE_C}$s.

Another heuristic-based algorithm for operation mode and resource allocation in D2D communication has been proposed in [SJWL13]. The proposed algorithm is based on particle swarm optimization to improve the system throughput with the minimum data rate requirements.

In [FLYW$^+$13], the authors have proposed a resource allocation scheme for D2D communication in cellular network to guarantee QoS requirements. The BS performs a resource allocation scheme in three stages: i) check the SINR requirements for D2D communication, ii) apply power control for the $\mathrm{UE_D}$, and iii) apply resource allocation for $\mathrm{UE_C}$s and $\mathrm{UE_D}$s.

The impact of multiple $\mathrm{UE_D}$ pairs and $\mathrm{UE_C}$s (in same macro cell) on throughput of each UE_D pair has been studied in [OQD13]. The authors have considered only the interference between UE_D pairs and assumed no interference generated to/from the cellular network due to CR capabilities within each UE_D pair.

Applying CR technique in D2D communication has been modelled and analysed in [SH14]. The cognitive UE_D-Tx uses the DL phase, which are not used by nearby BSs, to communicate with UE_D-Rx. Thus, no interference to the UE_Cs in the DL transmission is introduced.

2.7.4 Reliability

Different schemes have been proposed to improve the reliability of the D2D communication. An interference management scheme has been proposed in [MSL+11] to increase the performance of D2D communication without reducing the transmit power of cellular nodes. The authors propose a re-transmission of interference from the BS to UE_D-Rxs to generate the desired strength of the interference. Thus, the UE_D-Rxs can remove it by using an interference cancellation method.

In [KLA13], the authors have proposed a distributed power control scheme for multi-hop D2D communication. The proposed scheme uses a predefined interference margin of the UE_C to adjust the transmit power of UE_D. The results show that the outage probability of D2D links is inverse proportional to the path loss component of the D2D link.

2.7.5 Spectrum Utilization and Fairness

To improve the spectrum utilization of the system, D2D communication has been introduced into the cognitive networks underlying the cellular networks to increase the spectrum utilization [CDY+12]. The SUs either use the idle spectrum in the cellular network to perform CM through the BS, or they perform D2D communication within NOM using underlay paradigm due to the lack of idle spectrum. The authors propose game theory to perform individual mode selection by each SU. The results show an improvement in the spectrum utilization up to 50% and 500%, compared to pure CM and NOM, respectively.

Another research has proposed an innovation resource allocation scheme based on sequential second price auction to improve the efficiency of D2D communication as an underlay in DL cellular networks [XSH+12]. The proposed algorithm shows improvement in the system sum rate, efficiency, and fairness.

2.8 Summary

The presented work in the literature is a step towards enhancing the performance of D2D communication in cellular networks. However, there are some challenges that have not been solved and have negative impacts on the performance of the D2D communication and the system spectral efficiency in cellular networks. Some of these challenges include:

- The interference at $\mathrm{UE_D}$s from the cellular system is still an issue due to the priority of cellular communication during the resource allocation.
- High signalling overhead in the D2D communication which occurs at every link establishment/re-configuration process, as well as during the transmission because of the dynamic radio environment, the geographical positions of the cellular entities and the $\mathrm{UE_C}$'s activities.
- Low $\mathrm{UE_C}$ activity within the assigned resources which leads to low spectrum utilization, especially in crowded urban environments in which a major part of the resource blocks is reserved for the $\mathrm{UE_C}$s.

To overcome the aforementioned challenges, there is a need to investigate the possible access paradigms to improve the performance of D2D communication under the dynamic radio environment and the interference from the cellular entities. The investigation includes studying the radio resource management and defining the sources of degradation in the performance so as to solve it. Also, there is a need to define a scheme for adapting and reconfiguring D2D communication link autonomously under dynamic radio environments.

In the next chapter, the access paradigms are explained and their weaknesses are discussed in details. Then a new access paradigm is introduced for D2D communication to improve its spectral efficiency.

3 Analytical Model of System Capacity for D2D Communication

Contents

Improving the performance of cellular system is the main goal which pushes the researchers toward the integration of D2D communication within the cellular networks by sharing the resources (in frequency domain). One of the main metrics to evaluate the performance of D2D communication within cellular system is the spectral efficiency. Different factors have influences (negative and positive) on the spectral efficiency of the D2D communication, and these factors ultimately affect the performance of the total spectral efficiency of the system (D2D and cellular communications). Some of these factors are related to the cellular entities (BS and $\mathrm{UE_C}$s), as well as the D2D communication such as their geographical positions in the cell, the minimum acceptable SINR (threshold SINR), transmit power and the distance between the communicating pair. However, the main factor is the path loss between the cellular entities and UE_D pair which reflects an image about the amount of intra-cell interference between the cellular entities and the UE_Ds. This factor has the main negative influence on the total spectral efficiency of the system.

This chapter introduces a detailed study of the total spectral efficiency in the cell using different access paradigms to integrate D2D communication with the cellular system by sharing the resources. Then, the relationship between geographical positions in the cell (UE_D and the cellular entities) and the total spectral efficiency is modeled in a closed-form expression. The presented relationship aids in defining the positions in the cell in which the D2D communication can take place. Then, hybrid access paradigm is proposed to efficiently invest portion of the frequency resources (overlay paradigm) as well underlay paradigm to improve the total spectral efficiency. This study is presented for single and multiple UE_D pairs which attempt to access single resource block.Later, enumerations has been applied to evaluate the performance of different access paradigms in terms of the total spectral efficiency within D2D communication. The impacts of the aforementioned factors on the total spectral efficiency are studied under different access paradigms.

This chapter is organized as follows: first, the system model is presented. Two use cases are defined according to the number of UE_D pairs. Then, the spectral efficiency using underlay, overlay and hybrid access paradigms are described in detail with a closed-form expression for spectral efficiency based on geographical positions. To validate the proposed access paradigm, a numerical simulation is perform to evaluate performance of both D2D communication using different access paradigms.

3.1 System Model

Sharing cellular resources with D2D communication generates interference at the cellular system, which has a negative influence on their SINR. This crucial issue has been discussed in literature. Many previous work proposed different methodologies and algorithms to avoid interference with cellular system, such as spectrum allocation algorithms, power management schemes, time scheduling, etc. which achieved a reduction of interference at cellular systems. Another issue is that the D2D communication may suffer from interference from the C-Tx, which degrade their SINR .

In this chapter, the studied system model consists of a cellular system with UE_D pair, as shown in Fig 3.1. The cellular network is represented by 7 neighbor macro cells of a

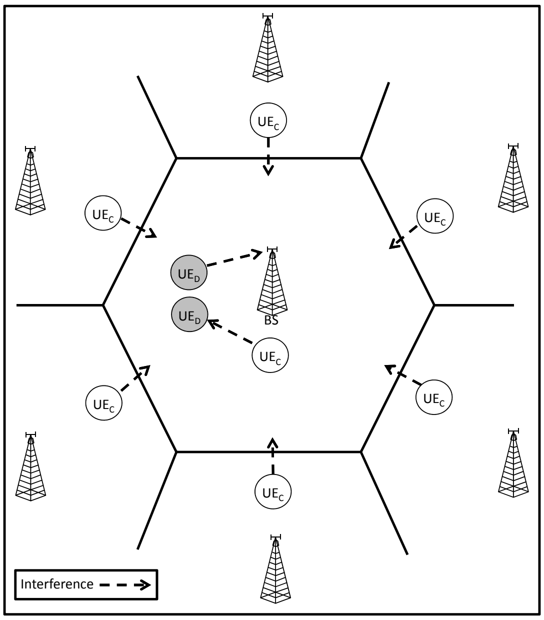

Figure 3.1: System model of D2D Communication

radius R_C with a frequency reuse factor of 1. Each cell consists of a BS and a number of $\mathrm{UE_C}$s distributed in the cell. The BS is equipped with omnidirectional antenna and its spectrum band is divided into UL and DL sub-bands using the Frequency Division Duplex (FDD) scheme. Each band is divided into number of sub-channels with frequency f_C. The system uses Time Division Multiple Access (TDMA) to generate Resource Blocks (RBs) which represent the time slots in which the $\mathrm{UE_C}$ uses different f_Cs. The transmit power of cellular entities ($\mathrm{UE_C}$ in UL and BS in DL) is defined according to the threshold SINR Γ_C and the d_C^{γ}. In addition to the $\mathrm{UE_C}$s, there are $\mathrm{UE_D}$s which attempt to achieve direct communication in order to off-load some data traffic from the cellular network. The BS defines the positions of $\mathrm{UE_C}$s and $\mathrm{UE_D}$s in the cell by defining the the Signal Strength (SS) and Angle of Arrival (AoA) of their signals. Thus, BS determines the path loss between the $\mathrm{UE_C}$ and $\mathrm{UE_D}$s, as well as the itself.

To have a clear view of D2D communication in the cell, there is a need to study the spectral efficiency of D2D communication η_D and the total spectral efficiency η_{total} to show the performance of D2D communication over the macro cell in presence of intra-cell interference and inter-cell interference (from neighbor cells). The cell in the middle is the cell of interest (CoI) which includes $\mathrm{UE_C}$s and the $\mathrm{UE_D}$s.

According to the number of $\mathrm{UE_D}$ pairs in the cell, the intra-cell interference and the η_{total} changes dramatically at different positions in the CoI. To study the behavior of

η_{total} within different number of $\mathrm{UE_D}$s, two use cases are studied in details:

1. Use case 1: Single RB with Single D2D Pair (SRSP)
2. Use case 2: Single RB with Multiple D2D Pairs (SRMP)

The total spectral efficiency is studied with these use cases using three different access paradigms: i) underlay; ii) overlay; and iii) hybrid (underlay-overlay).

3.2 Use Case 1: Single RB with Single D2D Pair (SRSP)

In this use case, the cellular system in CoI has one RB allocated to one $\mathrm{UE_C}$. Also, one $\mathrm{UE_D}$ pair is available and requests to perform D2D communication using this RB. Such integration requires an access paradigm to share RB in the cell without generating a harmful interference at both cellular entities and $\mathrm{UE_D}$s.

In the next subsections, the total spectral efficiency is expalined in details using the aforementioned access paradigms.

3.2.1 Underlay

The Underlay paradigm (Un) is the widely used to perform D2D communication in the literature. The goal of this paradigm is to reuse the RB for D2D communication without interfering the cellular receiver (C-Rx) [KLA13, FLYW⁺13, BBGS13].

To avoid a harmful interference at cellular system, the researchers in [KA08, KLA13] proposed an interference margin k at the cellular system in such a way that:

$$\frac{P_C d_C^{-\gamma}}{\sigma_n^2} \geq k\Gamma_C, \tag{3.1}$$

where P_C is the transmit power of cellular transmitter (C-Tx), Γ_C is the minimum required SINR at the C-Rx (BS in UL and $\mathrm{UE_C}$ in DL), $d_C^{-\gamma}$ is the cellular path loss (between BS and $\mathrm{UE_C}$) and σ_n^2 is the noise power.

Thus, the P_C can be formulated as:

$$P_C \geq k\Gamma_C \sigma_n^2 d_C^{\gamma} \tag{3.2}$$

By performing D2D communication which reuses RB with the cellular entities using Un paradigm, Eq. 3.1 is reformulated as:

$$\frac{P_C d_C^{-\gamma}}{P_D d_{DC}^{-\gamma} + \sigma_n^2} \geq \Gamma_C, \tag{3.3}$$

where P_D is the transmit power of UE_D Transmitter (UE_D-Tx) and $d_{DC}^{-\gamma}$ is the path loss between the UE_D-Tx and C-Rx.

While the only source of interference to the cellular network is the UE_D-Tx (neglecting the inter-cell interference from neighbor cells which are using the same RB), the upper bounds of its transmit power $P_{D_{max}}$ can be derived by substituting Eq. 3.2 into Eq. 3.3 and reformulate it [KA08, KLA13]:

$$P_{D_{max}} \leq (k-1)\sigma_n^2 d_{DC}^{\gamma}, \tag{3.4}$$

However, The P_D must fulfill the threshold SINR of D2D communication Γ_D:

$$\frac{P_D d_D^{-\gamma}}{\sum_{i=1}^{N_C} P_{C_i} d_{C_i D}^{-\gamma} + \sigma_n^2} \geq \Gamma_D, \tag{3.5}$$

where N_C is the number of C-Txs (in the CoI and the neighbor cells which are using the same RB) and P_{C_i} is the transmit power of i^{th} C-Tx and $d_{C_i D}^{\gamma}$ is the path loss between the i^{th} C-Tx and UE_D-Rx.

By substituting Eq. 3.2 into Eq. 3.5, the lower bound of UE_D-Tx transmit power $P_{D_{min}}$ is formulated as:

$$P_{D_{min}} \geq \Gamma_D \; d_D^{\gamma} \; \sigma_n^2 \; \left(k \; \Gamma_C \sum_{i=1}^{N_C} \left(\frac{d_{C_i}}{d_{C_i D}}\right)^{\gamma} + 1\right) \tag{3.6}$$

Thus, the indication function of performing D2D communication using Un access paradigm In^{Un} in the CoI is based on:

$$\frac{P_D d_D^{-\gamma}}{\sum_{i=1}^{N_C} P_{C_i} d_{C_i D}^{-\gamma} + \sigma_n^2} \geq \Gamma_D, \tag{3.7}$$

By substituting Eq. 3.2 and 3.4 in Eq. 3.7, In^{Un} can be reformulated as:

$$In^{Un} = \begin{cases} 1 & \text{if} \quad \frac{\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k \; \Gamma_C \sum_{i=1}^{N_C} \left(\frac{d_{C_i}}{d_{C_i D}}\right)^{\gamma} + 1} \geq \frac{\Gamma_D}{k-1} \\ 0 & \text{else} \end{cases} \tag{3.8}$$

It is clear from Eq. 3.8 that the In^{Un} depends on the d_C^{γ}, d_{CD}^{γ}, d_{DC}^{γ}, and d_D^{γ} which represent mainly the geographical positions of UE_D pair and UE_C in the CoI (considering no obstacles in CoI).

By transmitting data using D2D communication with the upper bound of transmit power ($P_D = P_{Dmax}$) and substituting Eqs. 3.2 and 3.4 in Eq. 3.5, the spectral efficiency of D2D communication using Un paradigm η_D^{Un} is:

$$\eta_D^{Un} = In^{Un} \ \log_2 \left(1 + \frac{(k-1) \ (\frac{d_{DC}}{d_D})^{\gamma}}{k\Gamma_C \ \sum_{i=1}^{N_C} (\frac{d_{C_i}}{d_{C_iD}})^{\gamma} + 1} \right) \tag{3.9}$$

The spectral efficiency of a cellular system in CoI η_C^{Un} is:

$$\eta_C^{Un} = \begin{cases} \log_2(1+\Gamma_C) & \text{if } In^{Un} = 1 \\ \log_2(1+k\ \Gamma_C) & \text{if } In^{Un} = 0 \end{cases} \tag{3.10}$$

By considering In_D^{Un} as an indicator for D2D communication using Un paradigm, the generic formula of the achievable SINR at C-Rx in Eq. 3.1 can be modeled as:

$$\frac{P_C d_C^{-\gamma}}{In^{Un} P_D d_{DC}^{-\gamma} + \sigma_n^2} \geq (k - In^{Un}(k-1))\Gamma_C \tag{3.11}$$

By defining the geographical positions and the QoS requirements in the cell, the CoI is divided into many regions in which are classified as:

1. Region of D2D communication using Un access paradigm $REG_{D\&C}$. In this region, the η_{total} is:

$$\eta_{total}^{Un} = In_D^{Un} \ \log_2 \left(1 + \frac{(k-1) \ (\frac{d_{DC}}{d_D})^{\gamma}}{k\Gamma_C \ \sum_{i=1}^{N_C} (\frac{d_{C_i}}{d_{C_iD}})^{\gamma} + 1} \right) + \log_2(1+\Gamma_C) \tag{3.12}$$

The D2D communication is performed in this region if:

- $In_D^{Un} = 1$:

$$\frac{\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k \ \Gamma_C \sum_{i=1}^{N_C} \left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma} + 1} \geq \frac{\Gamma_D}{k-1} \tag{3.13}$$

- The η_D^{Un} is greater than or equal to the reduction in the cellular spectral efficiency:

$$\eta_D^{Un} \geq \log_2 \left(\frac{1 + k \ \Gamma_C}{1+\Gamma_C} \right) \tag{3.14}$$

By substituting Eq. 3.9 in Eq. 3.14:

$$\frac{(k-1)\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\ \Gamma_C\ \sum_{i=1}^{N_C}\left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma}+1} \geq \frac{1+k\Gamma_C}{1+\Gamma_C} \tag{3.15}$$

2. Region of cellular communication only REG_C. In this region, the η_{total} is:

$$\eta_{total} = \log_2(1+k\ \Gamma_C) \tag{3.16}$$

The D2D communication is not performed in this region if:

- $In_D^{Un} = 0$:

$$\frac{\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\ \Gamma_C \sum_{i=1}^{N_C}\left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma}+1} < \frac{\Gamma_D}{k-1} \tag{3.17}$$

- The η_D^{Un} is less than the reduction in the cellular spectral efficiency:

$$\frac{(k-1)\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\ \Gamma_C\ \sum_{i=1}^{N_C}\left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma}+1} < \frac{1+k\Gamma_C}{1+\Gamma_C} \tag{3.18}$$

3.2.2 Overlay

In overlay access paradigm (Ov) the BS divides RB (in frequency dimension) between the UE_Ds and UE_C orthogonally [YTDR09, DYRJ10, YSCA13]. Such paradigm doesn't make intra-cell interference between the cellular entities and the UE_Ds. Applying Ov access paradigm is considered for an OM and CM of operation. In this section, OM is the operation mode of D2D communication.

The P_C is computed as in Eq. 3.2.

Although there is no intra-cell interference in the CoI , the UE_D-Tx should not make a harmful interference at the C-Rxs of the neighbor cells. Thus, the $P_{D_{max}}$ is adapted to the closest C-Rx in neighbor cells according to Eq. 3.4 as:

$$P_{D_{max}} \leq (k-1)\sigma_n^2 d_{DC}^{\gamma}, \tag{3.19}$$

where d_{DC}^{γ} is the path loss between UE_D-Tx and the closest C-Rx in the neighbor cells, which is:

$$d_{DC}^{\gamma} = \arg\min_i d_{DC_i}^{\gamma}, \quad i = 1, 2, .., N_C - 1 \tag{3.20}$$

where N_C-1 is the number of C-Tx in the neighbor cells which are using the same RB.

Although the D2D communication has no intra-cell interference (from the cellular entities in CoI) in this paradigm, it still suffer from inter-cell interference (from neighbor cells). The achievable SINR in D2D communication Γ is:

$$\frac{P_D d_D^{-\gamma}}{k\Gamma_C \sigma_n^2 \sum\limits_{i=1}^{N_c-1} \left(\frac{d_{C_i}}{d_{C_i D}}\right)^{\gamma} + \sigma_n^2} \geq \Gamma_D, \tag{3.21}$$

Thus, the lower bound of $\mathrm{UE_D}$-Tx transmit power $P_{D_{min}}$ is:

$$P_{D_{min}} \geq \Gamma_D d_D^{\gamma} \sigma_n^2 \left(k\Gamma_C \sum_{i=1}^{N_C-1} \left(\frac{d_{C_i}}{d_{C_i D}}\right)^{\gamma} + 1 \right) \tag{3.22}$$

Thus, the indication function of D2D communication using Ov access paradigm In^{Ov} in the CoI is based on:

$$\frac{P_D d_D^{-\gamma}}{\sum_{i=1}^{N_C-1} P_{C_i} d_{C_i D}^{-\gamma} + \sigma_n^2} \geq \Gamma_D, \tag{3.23}$$

By substituting Eq. 3.2 and 3.19 in Eq. 3.23, In^{Ov} can be reformulated as:

$$In^{Ov} = \begin{cases} 1 & \text{if} \quad \dfrac{(k-1)\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\Gamma_C \ \sum_{i=1}^{N_C-1} \left(\frac{d_{C_i}}{d_{C_i D}}\right)^{\gamma} + 1} \geq \frac{\Gamma_D}{k-1} \\ 0 & \text{else} \end{cases} \tag{3.24}$$

It is clear from Eq. 3.24 that the In^{Ov} depends on the $d_{C_i}^{\gamma}$, $d_{C_i D}^{\gamma}$ and $d_{DC_i}^{\gamma}$ of the closest i^{th} C-Tx and C-Rx in the neighbor cell, as well as d_D^{γ} which represent the geographical positions of $\mathrm{UE_D}$ pair in the CoI and $\mathrm{UE_C}$s in the neighbor cells.

According to Shannon theorem, the spectral efficiency of D2D communication using Ov paradigm η_D^{Ov}(with half of RB is dedicated to D2D communication) is:

$$\eta_D^{Ov} = \frac{1}{2} In_D^{Ov} \ \log_2 \left(1 + \frac{(k-1)\left(\frac{d_{DC_i}}{d_D}\right)^{\gamma}}{k\Gamma_C \ \sum_{i=1}^{N_C-1} \left(\frac{d_{C_i}}{d_{C_i D}}\right)^{\gamma} + 1} \right) \tag{3.25}$$

The spectral efficiency of a cellular network within D2D communication Ov paradigm η_C^{Ov} is:

$$\eta_C = \begin{cases} \frac{1}{2} \log_2(1 + k \ \Gamma_C) & \text{if } In^{Ov} = 1 \\ \log_2(1 + k \ \Gamma_C) & \text{if } In^{Ov} = 0 \end{cases} \tag{3.26}$$

By defining the geographical positions,the QoS requirements in the cell, the COI is divided into many regions in which each is classified as:

1. Region of D2D communication $REG_{D\&C}$. In this region, the η_{total}^{Ov} is:

$$\eta_{total} = \frac{1}{2} In_D^{Ov} \ \log_2 \left(1 + \frac{(k-1)\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\Gamma_C \ \sum_{i=1}^{N_C-1} \left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma} + 1} \right) + \frac{1}{2}\log_2(1 + k\ \Gamma_C) \quad (3.27)$$

The D2D communication is performed in this region if:

- $In_D^{Ov} = 1$:

$$\frac{\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\Gamma_C \ \sum_{i=1}^{N_C-1} \left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma} + 1} \geq \frac{\Gamma_D}{k-1} \quad (3.28)$$

- The η_D^{Ov} is greater than or equal to the reduction in the cellular spectral efficiency:

$$\eta_D^{Ov} \geq \frac{1}{2}\log_2(1 + k\ \Gamma_C) \quad (3.29)$$

By substitute Eq. 3.25 in 3.29:

$$\frac{\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\Gamma_C \sum_{i=1}^{N_C-1} \left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma}} \geq \frac{k\Gamma_C}{k-1} \quad (3.30)$$

2. Region of cellular communication only REG_C. In this region, the η_{total}^{Ov} is:

$$\eta_{total}^{Ov} = \log_2(1 + k\ \Gamma_C) \quad (3.31)$$

The D2D communication is not performed in this region if:

- $In_D^{Ov} = 0$:

$$\frac{\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\Gamma_C \ \sum_{i=1}^{N_C-1} \left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma} + 1} < \frac{\Gamma_D}{k-1} \quad (3.32)$$

- The η_D^{Un} is less than the reduction in the cellular spectral efficiency:

$$\frac{\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\Gamma_C \sum_{i=1}^{N_C-1} \left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma}} < \frac{k\Gamma_C}{k-1} \quad (3.33)$$

3.2.3 Hybrid (Underlay-Overlay)

In Underlay-Overlay (UnOv) access paradigm, the BS decides one of the aforementioned paradigms according to the positions of $\mathrm{UE_C}$s and $\mathrm{UE_D}$ pair in the CoI (position-based access paradigm) to achieve the maximum η_{total}^{UnOv}.

Thus, the CoI is divided into different regions which are classified as:

1. Region of D2D communication using Un access paradigm $REG_{D\&C}$. In this region, the η_{total}^{UnOv} is as in Eq. 3.12. The D2D communication is performed in this region if:

   - $In^{Un} = 1$ as in Eq. 3.8.
   - The improvement in the η_{total}^{UnOv} using Un access paradigm is greater than the reduction in η_C as in Eq. 3.15.
   - The improvement in the η_{total}^{UnOv} using Un access paradigm is greater than the improvement using Ov access paradigm:

   $$\eta_D^{Un} + \log_2(1 + \Gamma_C) \geq \eta_D^{Ov} + \frac{1}{2}\log_2(1 + k\ \Gamma_C) \tag{3.34}$$

   This region is located far from C-Tx ($\mathrm{UE_C}$ in UL and BS in DL) and C-Rx (BS in UL and $\mathrm{UE_C}$ in DL) in the CoI (cell edge if the inter-cell interference is low).

2. Region of D2D communication using Ov access paradigm $REG_{D\&C}$. In this region, the η_{total}^{UnOv} is modeled as in Eq. 3.31.The D2D communication is performed in this region if:

   - $In^{Ov} = 1$ as in Eq. 3.24.
   - The improvement in the η_{total}^{UnOv} using Ov access paradigm is higher than cellular mode as in Eq. 3.30.
   - The improvement in the η_{total}^{UnOv} using Ov access paradigm is higher than Un access paradigm:

   $$\eta_D^{Ov} + \frac{1}{2}\log_2(1 + k\ \Gamma_C) \geq \eta_D^{Un} + \log_2(1 + \Gamma_C) \tag{3.35}$$

   This region is located close from C-Tx ($\mathrm{UE_C}$ in UL and BS in DL) and C-Rx (BS in UL and $\mathrm{UE_C}$ in DL) in the CoI (cell center).

3. Region of cellular communication only REG_C. In this region, the η_{total}^{UnOv} is:

$$\eta_{total}^{UnOv} = \log_2(1 + k\ \Gamma_C) \tag{3.36}$$

The D2D communication is not performed in this region if:

- $In^{Un} = 0$ and $In^{Ov} = 0$.
- The improvement in the η_{total}^{UnOv} using cellular mode is higher than using Un access paradigms as in Eq. 3.18.
- The improvement in the η_{total}^{UnOv} using cellular mode is higher than using Ov access paradigms as in Eq. 3.33.

This region occurs at cell edge if the inter-cell interference is high and the d_D^{γ} is long. Also, it occurs in regions between $REG_{D\&C}$ using Un paradigm and $REG_{D\&C}$ using Ov paradigm.

3.3 Use Case 2: Single RB with Multiple D2D Pairs (SRMP)

In this use case, the CoI has one RB which is allocated to one $\mathrm{UE_C}$. Also, N_D number of $\mathrm{UE_D}$ pairs attempt to perform the communication using this RB. In the next subsections, η_{total} is studied using the aforementioned three different access paradigms.

3.3.1 Underlay

By applying Un paradigm in this use case, the multiple $\mathrm{UE_D}$ pairs attempt to reuse RB with the cellular network without generating harmful interference at C-Rx and other $\mathrm{UE_D}$ pairs. The P_C is modeled similar to Eq. 3.2.

In order not to generate harmful interference at C-Rx:

$$\sum_{j=1}^{N_D} P_{D_j} d_{D_jC}^{-\gamma} \leq (k-1)\ \sigma_n^2, \tag{3.37}$$

where P_{D_j} is the transmit power of the j^{th} $\mathrm{UE_D}$-Tx and $d_{D_jC}^{\gamma}$ is the path loss between the j^{th} $\mathrm{UE_D}$-Tx and C-Rx in CoI.

Thus, the upper bound of transmit power of the j^{th} $\mathrm{UE_D}$-Tx $P_{D_{jmax}}$ is modeled as:

$$P_{D_{jmax}} d_{D_jC}^{-\gamma} \leq x_j (k-1) \sigma_n^2, \tag{3.38}$$

where x_j is the portion of interference margin used by j^{th} $\mathrm{UE_D}$ pair ($\sum_{j=1}^{N_D} x_j = 1$).

Also, the lower bound of the transmit power of j^{th} UE$_{\mathrm{D}}$-Tx $P_{D_{jmin}}$ is:

$$P_{D_{jmin}} \geq d_{D_j}^{\gamma} \Gamma_D \sigma_n^2 \Bigg(k\Gamma_C \sum_{i=1}^{N_C} \left(\frac{d_{C_i}}{d_{C_i D_j}} \right)^{\gamma} + (k-1) \sum_{l=1, l\neq j}^{N_D} x_l \bigg(\frac{d_{D_l C}}{d_{D_{lj}}} \bigg)^{\gamma} + 1 \Bigg), \tag{3.39}$$

where $d_{C_i D_j}^{\gamma}$ is the path loss between the i^{th} C-Tx and j^{th} UE$_{\mathrm{D}}$-Rx, x_l is the portion of k used by l^{th} UE$_{\mathrm{D}}$ pair, $d_{D_l C}^{\gamma}$ is the path loss between the l^{th} UE$_{\mathrm{D}}$-Tx and the closest C-Rx and $d_{D_{lj}}$ is the path loss between the l^{th} UE$_{\mathrm{D}}$-Tx and the j^{th} UE$_{\mathrm{D}}$-Rx, assuming all the cellular entities (in CoI and neighbor cells) have the same Γ_C and k.

The indication function of D2D communication within the j^{th} UE$_{\mathrm{D}}$ pair using Un paradigm In_j^{Un} is:

$$In_j^{Un} = \begin{cases} 1 & \text{if } \dfrac{\left(\frac{d_{D_j C}}{d_{D_j}} \right)^{\gamma}}{k\Gamma_C \sum_{i=1}^{N_C} \left(\frac{d_{C_i}}{d_{C_i D_j}} \right)^{\gamma} + (k-1) \sum_{l=1,l\neq j}^{N_D} x_l \left(\frac{d_{D_l C}}{d_{D_{lj}}} \right)^{\gamma} + 1} \geq \frac{\Gamma_D}{(k-1)x_j} \\ 0 & \text{else} \end{cases} \tag{3.40}$$

Thus, the spectral efficiency of j^{th} D2D communication using Un access paradigm η_{Dj}^{Un} is:

$$\eta_{Dj}^{Un} = In_{Dj}^{Un} \log_2 \left(1 + \frac{x_j (k-1) \left(\frac{d_{D_j C}}{d_{D_j}} \right)^{\gamma}}{\Gamma_C k \sum_{i=1}^{N_C} \left(\frac{d_{C_i}}{d_{C_i D_j}} \right)^{\gamma} + \sum_{l=1,l\neq j}^{N_D} x_l \left(\frac{d_{D_l C}}{d_{Dlj}} \right)^{\gamma} + 1} \right) \tag{3.41}$$

By considering In_j^{Un}, the generic formula of achievable SINR at C-Rx is:

$$\frac{P_C d_C^{-\gamma}}{\sum_{j=1}^{N_D} In_j^{Un} x_j P_{Dj} d_{D_j C}^{-\gamma} + \sigma_n^2} \geq (k - In^{Un}(k-1))\Gamma_C, \tag{3.42}$$

where $In^{Un} = \arg max_j In_j^{Un}$ for j=1,..,N_D.

By defining the geographical positions of UE$_{\mathrm{C}}$ and UE$_{\mathrm{D}}$ pairs and their QoS requirements in the cell, the CoI is divided into many regions which are classified as:

1. Region of D2D communication using Un paradigm $REG_{D\&C}$. In this region, the η_{total}^{Un} is:

$$\eta_{total}^{Un} = \sum_{j=1}^{N_D} \eta_{Dj}^{Un} + \log_2(1+\Gamma_C) \tag{3.43}$$

The D2D communication is performed in this region if:

- $\forall_j, In_j^{Un} = 1$ as in Eq. 3.40.
- The total spectral efficiency of D2D communication pairs is greater or equal than the reduction in the cellular spectral efficiency using cellular mode:

$$\sum_{j=1}^{N_D} \log_2 \left(1+\frac{x_j(k-1)\left(\frac{d_{D_jC}}{d_{D_j}}\right)^{\gamma}}{\Gamma_C k \sum_{i=1}^{N_C} \left(\frac{d_{C_i}}{d_{C_iD_j}}\right)^{\gamma} + \sum_{l=1,l\neq j}^{N_D} x_l \left(\frac{d_{D_lC}}{d_{Dlj}}\right)^{\gamma} + 1}\right) \geq \log_2 \left(\frac{1+k\Gamma_C}{1+\Gamma_C}\right) \tag{3.44}$$

This region occurs if the $d_{D_j}^{\gamma}$ and d_C^{γ} are low,while $d_{CD_j}^{\gamma}$, $d_{D_jC}^{\gamma}$ (in the CoI and neighbor cells) and $d_{D_{lj}}^{\gamma}$ are high.

2. Region of cellular communication only REG_C. In this region, the η_{total}^{Un} is:

$$\eta_{total}^{Un} = \log_2(1 + k\ \Gamma_C) \tag{3.45}$$

The D2D communication is not performed in this region if:

- $\forall j, In_{Dj}^{Un} = 0$ if the Eq. 3.40 does not achieved for D2D pairs.
- The total spectral efficiency of D2D communication pairs is less than the reduction in the cellular spectral efficiency using cellular mode:

$$\sum_{j=1}^{N_D} \log_2 \left(1+\frac{x_j(k-1)\left(\frac{d_{D_jC}}{d_{D_j}}\right)^{\gamma}}{\Gamma_C k \sum_{i=1}^{N_C} \left(\frac{d_{C_i}}{d_{C_iD_j}}\right)^{\gamma} + \sum_{l=1,l\neq j}^{N_D} x_l \left(\frac{d_{D_lC}}{d_{Dlj}}\right)^{\gamma} + 1}\right) < \log_2 \left(\frac{1+k\Gamma_C}{1+\Gamma_C}\right) \tag{3.46}$$

This region occurs if the d_D and d_C are long,while d_{CD}, d_{DC} (in the CoI and neighbor cells) and $d_{D_{lj}}$ are short.

3.3.2 Overlay

In this access paradigm, the BS performs scheduling to divide the RB between the $\mathrm{UE_C}$s and N_D $\mathrm{UE_D}$ pairs in the CoI.

The P_C is modeled as in Eq. 3.2, while the upper bound of transmit power of j^{th} $\mathrm{UE_D}$-Tx $P_{Dj_{max}}$is modeled as in Eq. 3.38 and the $d_{D_jC}^{\gamma}$ is computed as in Eq. 3.20

The lower bound of of transmit power of j^{th} $\mathrm{UE_D}$-Tx $P_{Dj_{min}}$ and In_j^{Ov} for the j^{th} $\mathrm{UE_D}$ pair are modeled as in Eq. 3.22 and 3.23, respectively.

Thus, the spectral efficiency of j^{th} $\mathrm{UE_D}$ pair using Ov access paradigm η_{Dj}^{Ov} is:

$$\eta_{D_j}^{Ov} = \frac{1}{N_D+1} In_j^{Ov} \log_2\left(1 + \frac{x_j(k-1)\left(\frac{d_{D_jC}}{d_{D_j}}\right)^{\gamma}}{k\Gamma_C \sum_{i=1}^{N_C-1}\left(\frac{d_{C_i}}{d_{C_iD_j}}\right)^{\gamma} + 1}\right) \tag{3.47}$$

The spectral efficiency of cellular system in CoI η_C is:

$$\eta_C = \begin{cases} \frac{1}{N_D+1}\log_2(1 + k\ \Gamma_C) & \text{if } \forall j, In_j^{Ov} = 1 \\ \log_2(1 + k\ \Gamma_C) & \text{if } \forall j, In_j^{Ov} = 0 \end{cases} \tag{3.48}$$

By defining the geographical positions of $\mathrm{UE_C}$ and $\mathrm{UE_D}$ pairs, as well as their QoS requirements in the CoI, which may be divided into many regions which are classified as:

1. Region of D2D communication using Un paradigm $REG_{D\&C}$. In this region, the η_{total}^{Ov} is:

$$\eta_{total}^{Ov} = \sum_{j=1}^{N_D} \eta_{Dj}^{Ov} + \frac{1}{N_D+1}\log_2(1 + k\ \Gamma_C) \tag{3.49}$$

   The D2D communication is performed in this region if:

   - $\forall j, j = 1, .., N_D, In_j^{Ov} = 1$ if the Eq. 3.23.
   - The total spectral efficiency of D2D communication pairs is greater or equal to the reduction in η_C using cellular mode:

$$\sum_{j=1}^{N_D} \frac{1}{N_D+1}\log_2\left(1 + \frac{x_j(k-1)\left(\frac{d_{D_jC}}{d_{D_j}}\right)^{\gamma}}{\Gamma_C k \sum_{i=1}^{N_C-1}\left(\frac{d_{C_i}}{d_{C_iD_j}}\right)^{\gamma} + 1}\right) \geq \frac{N_D}{N_D+1}\log_2(1 + k\Gamma_C) \tag{3.50}$$

   This region occurs if the d_D and d_C are short,while d_{CD} and d_{DC} (in the neighbor cells) are long.

2. Region of cellular communication only REG_C. In this region, the η_{total}^{Ov} is:

$$\eta_{total}^{Ov} = \log_2(1 + k\ \Gamma_C) \tag{3.51}$$

   The D2D communication is not performed in this region if:

   - $\forall j, j = 1, .., N_D, In_j^{Ov} = 0$ if the condition in Eq. 3.23 has not been achieved.

- The total spectral efficiency of D2D communication pairs is less than the reduction in the cellular spectral efficiency using cellular mode:

$$\sum_{j=1}^{N_D} \frac{1}{N_D+1} \log_2 \left(1 + \frac{x_j(k-1)(\frac{d_{D_jC}}{d_{D_j}})^\gamma}{\Gamma_C k \sum_{i=1}^{N_C-1} \left(\frac{d_{C_i}}{d_{C_iD_j}}\right)^\gamma + 1}\right) < \frac{N_D}{N_D+1} \log_2(1 + k\Gamma_C) \tag{3.52}$$

This region occurs if the d_D and d_C are long,while d_{CD} and d_{DC} (in the neighbor cells) are short.

3.3.3 Hybrid (Underlay-Overlay)

By applying hybrid access paradigm for SRMP use case in BS, it has to schedule the usage of RB for N_D $\mathrm{UE_D}$ pairs and $\mathrm{UE_C}$. The BS divides the $\mathrm{UE_D}$ pairs into two groups: underlay group with N_D^{Un} number of $\mathrm{UE_D}$ pairs and overlay group with N_D^{Ov} number of $\mathrm{UE_D}$ pairs ($N_D = N_D^{Un} + N_D^{Ov}$).

For underlay group, the upper bound of transmit power of the j^{th} $\mathrm{UE_D}$-Tx $P_{D_{jmax}}^{Un}$ ($j = 1, .., N_D^{Un}$) is similar to Eq. 3.38. While the lower bound $P_{D_{jmin}}^{Un}$ is similar to Eq. 3.39.

The indicator function of D2D communication of j^{th} $\mathrm{UE_D}$ in underlay group In_j^{Un} is similar to Eq. 3.40.

Thus, the efficiency of j^{th} D2D communication pair in underlay η_{Dj}^{Un} is:

$$\eta_{Dj}^{Un} = In_j^{Un} \log_2 \left(1 + \frac{x_j(k-1)\left(\frac{d_{D_jC}}{d_{D_j}}\right)^\gamma}{\Gamma_C k \sum_{i=1}^{N_C} \left(\frac{d_{C_i}}{d_{C_iD_j}}\right)^\gamma + \sum_{l=1,l\neq j}^{N_D} x_l(k-1)\left(\frac{d_{D_lC}}{d_{Dlj}}\right)^\gamma + 1}\right) \tag{3.53}$$

For overlay group, the upper bound and the lower bound of transmit power of o^{th} $\mathrm{UE_D}$ ($o = 1, .., N_D^{Ov}$) $P_{D_{omax}}^{Ov}$ and $P_{D_{omin}}^{Ov}$ are computed as in Eq. 3.19, 3.22 and 3.23, respectively.

The indication function of D2D communication In_o^{Ov} is:

$$In_o^{Ov} = \begin{cases} 1 & \text{if} \quad \frac{x_o\left(\frac{d_{DC}}{d_D}\right)^\gamma}{k\Gamma_C \ \sum_{i=1}^{N_C-1} \left(\frac{d_{C_i}}{d_{C_iD}}\right)^\gamma + \sum_{l=1,l\neq o}^{N_D} x_l(k-1)\left(\frac{d_{D_lC}}{d_{Dlo}}\right)^\gamma + 1} \geq \frac{\Gamma_D}{k-1} \\ 0 & \text{else} \end{cases} \tag{3.54}$$

Thus, the spectral efficiency of the o^{th} D2D communication using Ov access paradigm

η_{Do}^{Ov} is:

$$\eta_{Do}^{Ov} = \frac{1}{N_D^{Ov}+1} In_o^{Ov} \log_2\left(1 + \frac{x_o(k-1)\left(\frac{d_{D_oC}}{d_{D_o}}\right)^{\gamma}}{k\Gamma_C \sum_{i=1}^{N_C}\left(\frac{d_{C_i}}{d_{C_iD_o}}\right)^{\gamma} + \sum_{l=1,l\neq o}^{N_D} x_l(k-1)\left(\frac{d_{D_lC}}{d_{Dlo}}\right)^{\gamma} + 1}\right) \tag{3.55}$$

The N_D^{Un} and N_D^{Ov} are decided by the BS depending on the maximum achievable η_{total}^{UnOv} which is influenced by x_j value (the portion of interference margin used per $\mathrm{UE_D}$s), their geographical positions and QoS requirements.

The CoI is divided into different regions according to the QoS and geographical positions of $\mathrm{UE_C}$ and $\mathrm{UE_D}$s in the CoI. These regions are classified into:

1. Region of D2D communication using underlay ($N_D = N_D^{Un}$) and cellular communication $REG_{D\&C}^{Un}$ in which the total spectral efficiency η_{total}^{UnOv} is:

$$\eta_{total}^{UnOv} = \sum_{j=1}^{N_D} \eta_{Dj}^{Un} + \log_2(1+\Gamma_C) \tag{3.56}$$

   The D2D communication is performed in this region if:

   - $\forall j, j = 1,..,N_D^{Un}, In_j^{Un} = 1$.
   - The total spectral efficiency of all D2D communication is greater than or equal to the reduction in the cellular communication as in Eq. 3.44

2. Region of D2D communication using overlay ($N_D = N_D^{Ov}$) and cellular communication $REG_{D\&C}^{Ov}$ in which the total spectral efficiency η_{total}^{UnOv} is:

$$\eta_{total}^{UnOv} = \sum_{j=1}^{N_D} \eta_{Dj}^{Ov} + \frac{1}{N_D+1}\log_2(1+\Gamma_C) \tag{3.57}$$

   The D2D communication is performed in this region if:

   - $\forall o, o = 1,..,N_D^{Ov}, In_o^{Ov} = 1$.
   - The total spectral efficiency of all D2D communication is greater than or equal to the reduction in the cellular communication as in Eq. 3.50

3. Region of which some of the D2D communication is performed using Un access paradigm, while the rest are performed using Ov access paradigm ($N_D = N_D^{Un} +$

N_D^{Ov}). The total spectral efficiency η_{total}^{UnOv} is:

$$\eta_{total}^{UnOv} = \sum_{j=1}^{N_D^{Un}} \eta_{Dj}^{Un} + \sum_{o=1}^{N_D^{Ov}} \eta_{Do}^{Ov} + \frac{1}{N_D^{Ov}+1} \log_2(1+\Gamma_C) \tag{3.58}$$

The D2D communication is performed in this region if:

- $\forall j, o, In_j^{Un} = 1$ and $In_o^{Ov} = 1$.
- The total spectral efficiency of all D2D communication (using both Un and Ov access paradigms) is greater than the reduction in the cellular communication:

$$\sum_{j=1}^{N_D^{Un}} \eta_{Dj}^{Un} + \sum_{o=1}^{N_D^{Ov}} \eta_{Do}^{Ov} \geq \log_2(1+k\Gamma_C) - \frac{1}{N_D+1} \log_2(1+\Gamma_C) \tag{3.59}$$

4. Region of some $\mathrm{UE_D}$ pair ($N_D^{Un} \subset N_D$) can perform D2D communication using Un access paradigm $REG_{1D\&C}$. The η_{total}^{UnOv} is:

$$\eta_{total}^{UnOv} = \eta_{D_j}^{Un} + \log_2(1+\Gamma_C) \tag{3.60}$$

The D2D communication is performed in this region if:

- $\exists j, In_j^{Un} = 1$.
- The total spectral efficiency of j^{th} D2D communication (using Un access paradigms) is greater than the reduction in the cellular communication:

$$\sum_{j=1}^{N_D^{Un}} \eta_{D_j} \geq \log_2\Big(\frac{1+k\ \Gamma_C}{1+\Gamma_C}\Big) \tag{3.61}$$

5. Region of only cellular communication REG_C. The η_{total}^{UnOv} is:

$$\eta_{total}^{UnOv} = \log_2(1+k\ \Gamma_C) \tag{3.62}$$

The D2D communication is not performed in this region if:

- $\forall j, o, In_j^{Un} = 0$ and $In_o^{Ov} = 0$.
- The total spectral efficiency of all D2D communication (using both Un and Ov access paradigms) is less than the reduction in the cellular communication:

$$\sum_{j=1}^{N_D^{Un}} \eta_{Dj}^{Un} + \sum_{o=1}^{N_D^{Ov}} \eta_{Do}^{Ov} < \log_2(1 + k\Gamma_C) - \frac{1}{N_D^{Ov} + 1} \log_2(1 + \Gamma_C) \tag{3.63}$$

3.4 Numerical Simulation

To evaluate the performance of D2D communication using the proposed access paradigms, a numerical simulation using MATLAB is performed in this section. The simulation scenario consists of a cellular network of 7 cells with an equal cell radius R_C and frequency reuse factor of 1 (inter-cell interference influences only the D2D communication). Each cell has a BS (with interference margin k, antenna gain A_{BS}, SINR threshold Γ_C) and a $\mathrm{UE_C}$ with path loss to BS d_C^γ. The CoI is the center cell which has $\mathrm{UE_D}$ pairs with a distance to BS d_{BSD}^γ. The D2D communication is performed using the UL band with a threshold SINR Γ_D. The C-Tx is the $\mathrm{UE_C}$ while the C-Rx is the BS. Table 3.1 shows the assumptions of the system model.

Table 3.1: Assumptions

Parameter	**Value**
Cell radius R_C (m)	10000
Threshold SINR of BS Γ_C (dB)	10
Threshold SINR of D2D/UD2D Γ_D (dB)	5
Path loss exponent γ	3
Interference margin k (dB)	3
Noise floor σ_n^2 (dBm)	-110
UE antenna gain A_{UE} (dBi)	2
BS antenna gain A_{BS} (dBi)	10

The aforementioned use cases are simulated, as shown in Fig. 3.2 (a) and (b).

3.5 Evaluation

Spectral efficiency is the metric which measures the maximum number of bits to be transmitted in duration of one second using one Hertz channel bandwidth without errors in the transmission. Many different factors have impacts on the system spectral efficiency in the cell using different access paradigm schemes. These factors are: i) the d_D; ii) the Γ_{BS} and k at different positions; iii) the geographical positions of cellular entities and the direct communicating pairs in CoI; and iv) the number $\mathrm{UE_D}$ pairs in the cell.

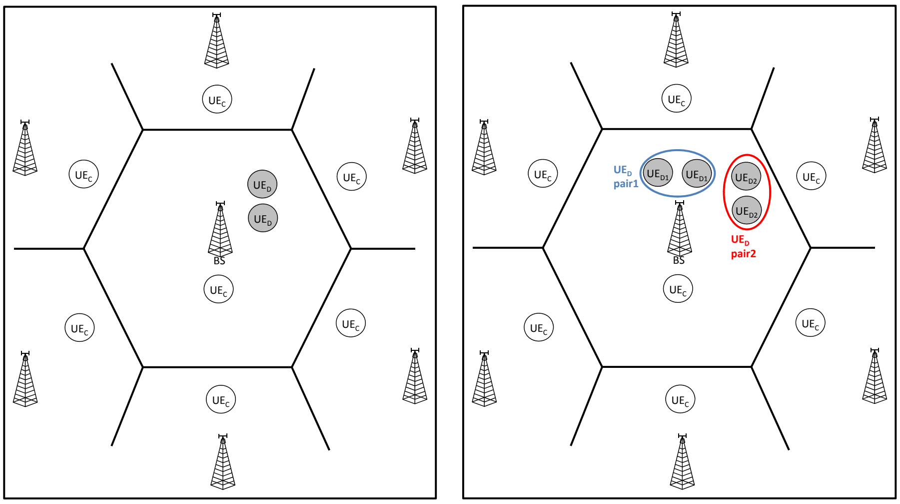

Figure 3.2: Simulation scenario of: (a) use case 1, (b) use case 2

In the next subsections, the impacts of these factors are shown in the use cases using different access paradigms.

3.5.1 Impact of Distance between the UE_D pair

The distance between the communication peer is inversely proportional to the received signal strength at the receiver according to the following equation:

$$P_r = P_t + A_t + A_r - \left(PL_0 + 10\gamma \log_{10}\left(\frac{d_0}{d}\right)\right) + sh, \tag{3.64}$$

where P_r is the received signal strength (dBm), P_t is the transmit power (dBm), A_t is the antenna gain of transmitter (dBi), A_r is the antenna gain of the receiver (dBi), d is the actual distance between the communicating peer (m) and sh is the shadowing effect (dB), PL_0 is the free space path loss of the of reference distance d_0 (dB):

$$PL_0 = 20 \log_{10}\left(\frac{4\pi d_0}{\lambda}\right), \tag{3.65}$$

where d_0 is the reference distance (1 m for indoor and 100 m for out door), λ is the wavelength of the signal (m).

The changing of distance/path loss between UE_D pair may lead to dramatically link failure at some positions in the CoI. The impact of d_D^{γ} on η_{total} at different positions of UE_D pair in CoI is studied under the aforementioned use cases using enumeration. The sh has been neglected in the following results. The step size between the positions of

UE_Ds is 20 m.

3.5.1.1 Use Case 1: SRSP

In this use case, single UE_D pair attempts to reuse the RB with cellular user by using four different access paradigms: i) Un paradigm; ii) Ov paradigm; and iii) UnOv paradigm.

Figure 3.3 (a), (b), (c), (d), (e) and (f) shows the η_{total} at each position of UE_D in the CoI with different d_D/R_C values (1% and 3%) using Un, Ov and UnOv access paradigms, respectively. The figure shows an outage in performance of η_{total} when the d_D/R_C is increased. The increment in d_D/R_C degrades the received signal strength at the UE_D-Rx, which may leads to not meet the constraint ($\Gamma < \Gamma_D$) and degrades η_D and η_{total}. The cell at each figure is divided into different regions which are classified into $REG_{D\&C}$ and REG_C according to the value of η_{total} and the applied access paradigm. The area of these regions are changed by varying the d_D which influence the Γ and η_D, as well as the η_{total}.

The Un paradigm increases the value of η_{total} at the cell edge ($REG_{D\&C}$), compared to Ov access paradigm. However, the Ov paradigm has $REG_{D\&C}$ with bigger area, compared to Un paradigm. By using UnOv access paradigm, the position of UE_D pairs in the cell is considered as a parameter in the decision of selecting which access paradigm to improve the η_{total}. Figure 3.3 (e) and (f) shows that UnOv outperforms Un and Ov paradigms in both η_{total} and the area of $REG_{D\&C}$ under different d_D.

Figure 3.4 shows the Cumulative Density Function (CDF) of the η_{total} using: i) Un; ii) Ov; and iii) UnOv access paradigms within d_D equals to 100m. The cdf of UnOv paradigm can be divided into two parts: i) the lower part which is similar to the CDF of Ov and represents the cdf of η_{total} at the cell center (using Ov); and ii) the upper part which is identical to the CDF of Un access paradigm and represents the CDF of η_{total} at the cell edge (using Un).

Figures 3.5 shows the area of $REG_{D\&C}$ regions in the CoI using Un, Ov and UnOv access paradigms. The UnOv paradigm outperforms both Un and Ov within different d_D values due to selecting the proper access paradigm according to the position of UE_C and UE_D pair. Thus, the impacts of intra-cell interference and limitation of P_D are reduced at many positions in the cell.

3.5.1.2 Use Case 2: SRMP

In this use case, two UE_D pairs attempt to use the RB with UE_C. One UE_D pair is stationary, while the other one attempts to use the RB at each position in the COI. Both

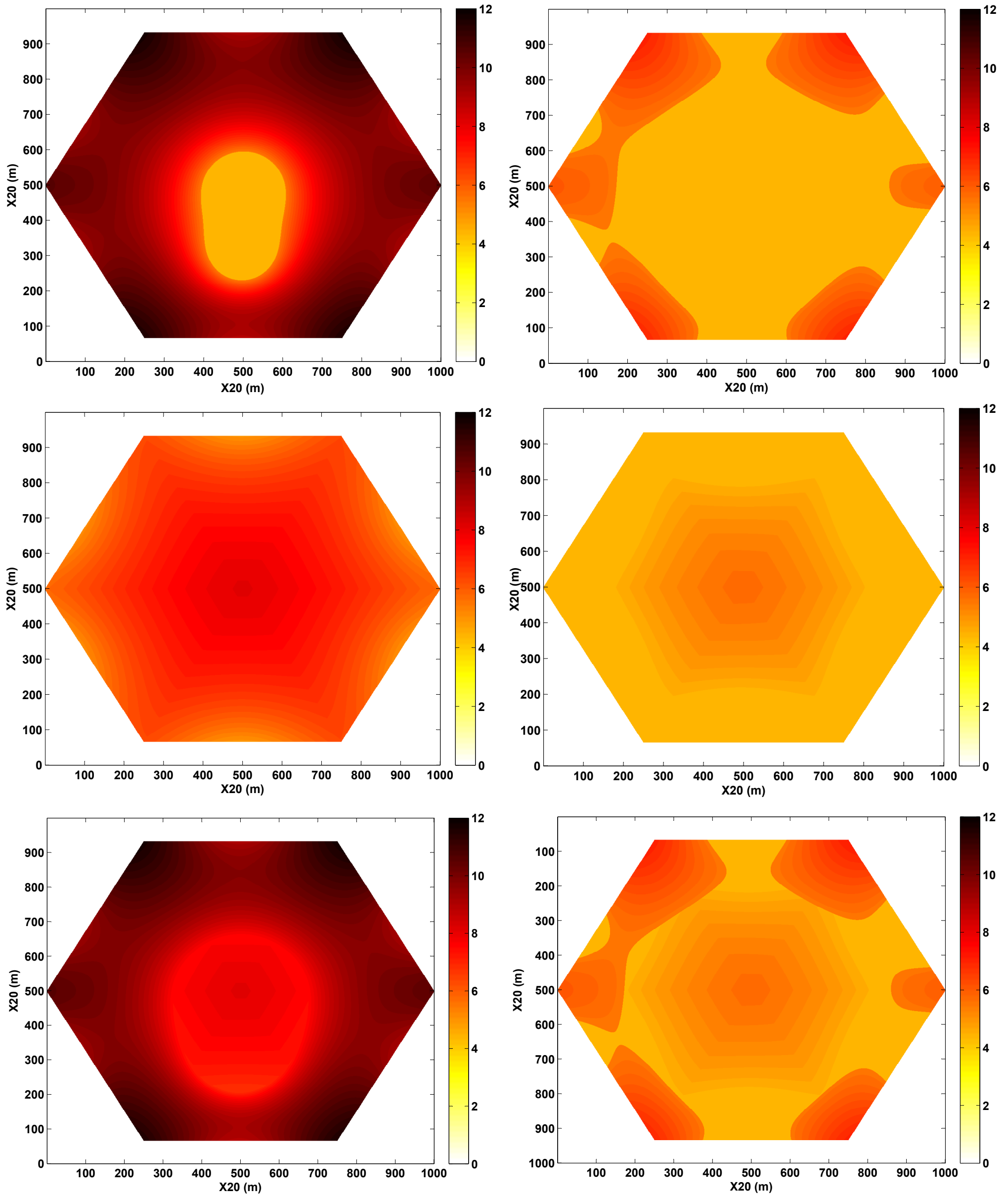

Figure 3.3: η_{total} of use case 1 at different positions of $\mathrm{UE_D}$ using different access paradigm in CoI with d_D/R_C of: (a) 1% using Un; (b) 3% using Un; (c) 1% using Ov; (d) 3% using Ov; (e) 1% using UnOv; and (f) 3% using UnOv

$\mathrm{UE_D}$ pairs use three different access paradigms: i) Un paradigm; ii) Ov paradigm; and iii) UnOv paradigm.

Figures 3.6 (a), (b), (c), (d), (e) and (f) show the η_{total} of use case 2 at each position in CoI with different d_D/R_C values (1% and 3%) using Un, Ov and UnOv access paradigms,

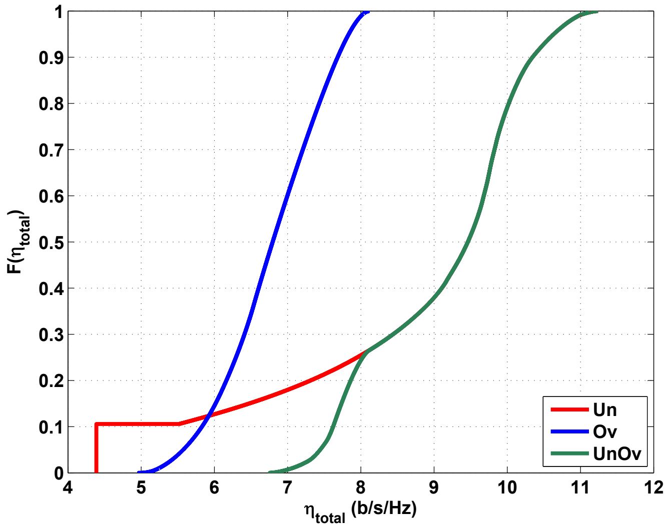

Figure 3.4: Comparison of η_{total} using Un, Ov and UnOv access paradigms with d_D=100 m in use case 1

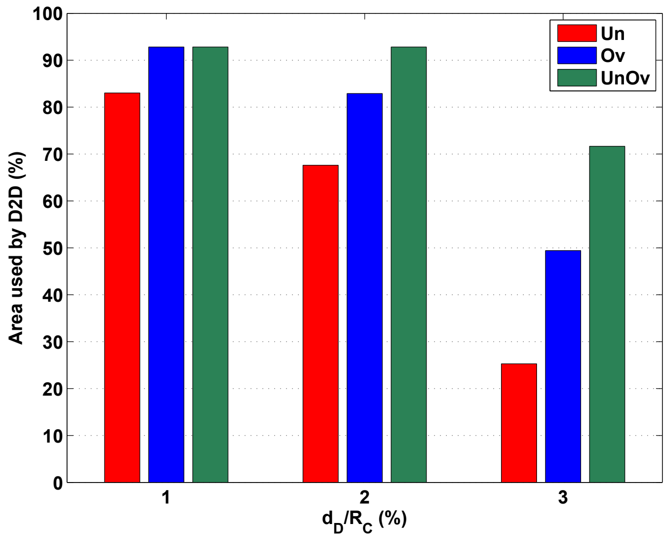

Figure 3.5: Comparison of the area used for D2D communication in the cell using Un and UnOv mode over different d_D in use case 1

respectively. Similar to SRSP, the figures show an outage in performance η_{total} when the d_D/R_C is increased due to similar reasons (intra-cell interference, inter-cell interference and limitation in the P_D) which degrade Γ, and influence the η_{total}. The cell at each figure is divided into different regions which are classified into: i) REG_C; ii) $REG_{1D\&C}$ which includes one D2D communication from the $\mathrm{UE_D}$ pairs; and iii) $REG_{D\&C}$ which

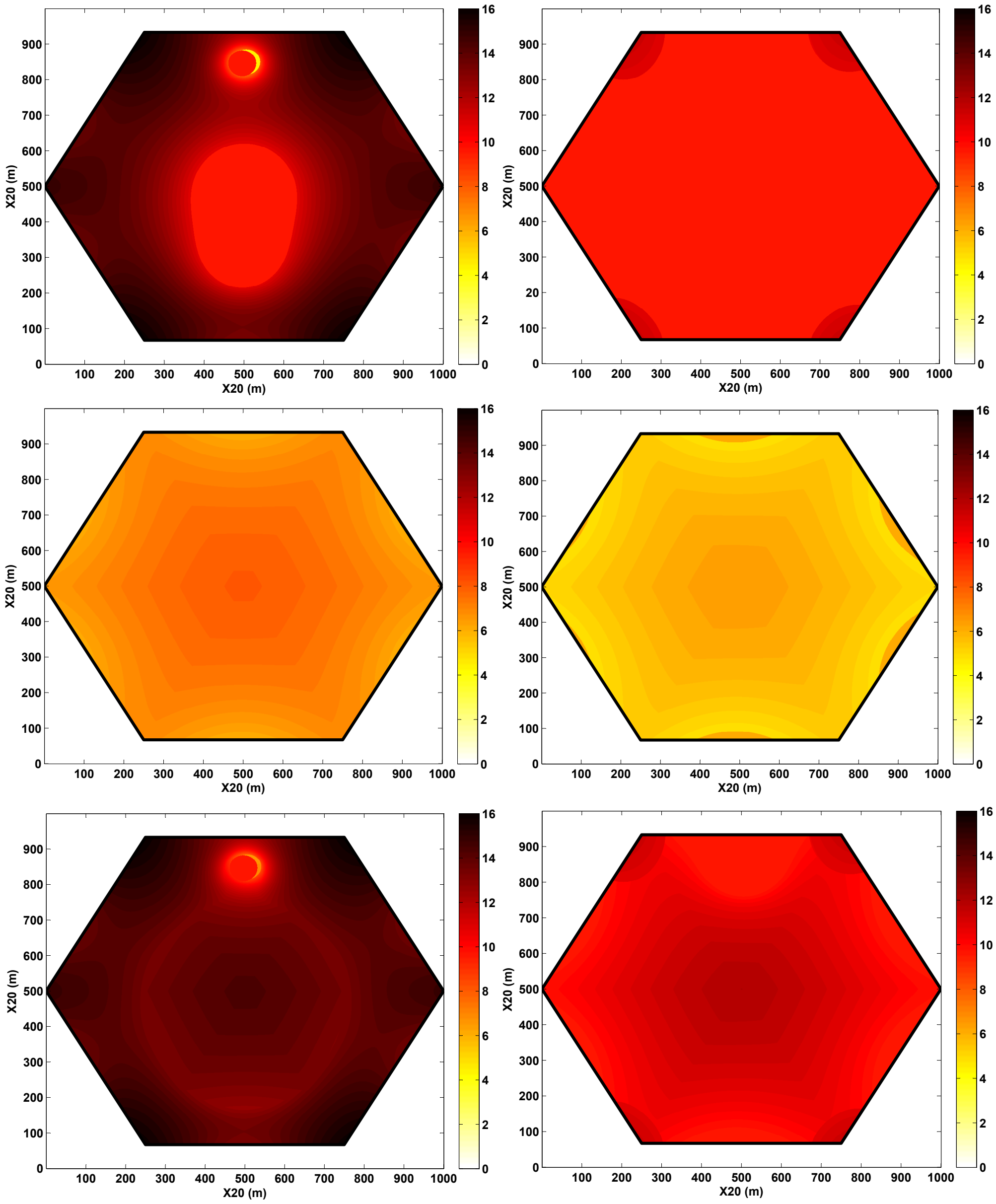

Figure 3.6: η_{total} of use case 2 at different positions of $\mathrm{UE_D}$ pair the cell with d_D/R_C of: (a) 1% using Un paradigm, (b) 3% using Un paradigm, (c) 1% using Ov paradigm, (d) 3% using Ov paradigm, (e) 1% using UnOv paradigm, and (f) 3% using UnOv paradigm

includes two D2D communication. The discrimination between these regions depends on the value of η_{total}. However, the area of these regions are changed by varying the d_D which influence the Γ and η_D, as well as the η_{total}.

The Un access paradigm outperforms Ov paradigm in η_{total} at regions $REG_{D\&C}$ due to reusing the RB in non orthogonal manner which allows the $\mathrm{UE_D}$ pairs to reuse the full RB, as shown in Fig. 3.6 (a) and (b). However, the Ov outperforms the Un paradigm at $REG_{D\&C}$ region due to the sharing the RB in orthogonal manner between the $\mathrm{UE_D}$ pairs and the $\mathrm{UE_C}$ (in frequency dimension), as shown in Fig. 3.6 (c) and (d).

To combine the improvement in η_{total} and the area of $REG_{D\&C}$ which are achieved by Un and Ov paradigms, respectively, the UnOv paradigm can be used to decide the best access paradigm to select according to the positions of $\mathrm{UE_D}$ pairs and $\mathrm{UE_C}$ in the cell, as well as the other parameters. Thus, the η_{total} and the area of $REG_{D\&C}$ are increased every where except at region where $\mathrm{UE_D}$ pairs are close to each others, as shown in Fig. 3.6 (e) and (f).

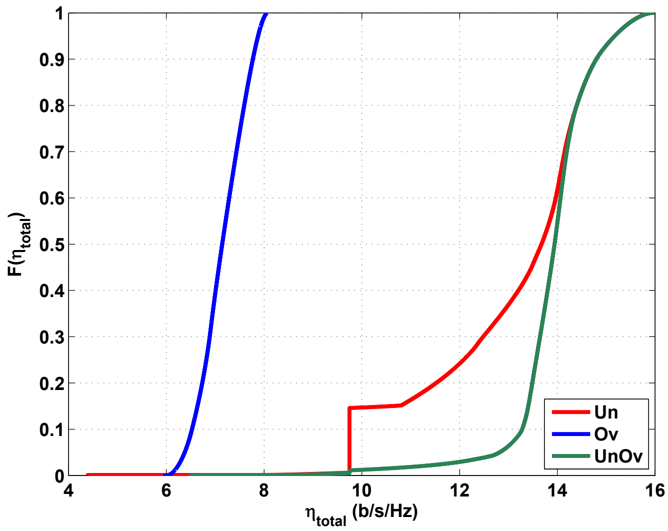

Figure 3.7: Comparison of η_{total} using Un, Ov and UnOv access paradigms with d_D=100 m in use case 2

Figure 3.7 shows the CDF of the η_{total} using: i) Un; ii) Ov; and iii) UnOv access paradigms within d_D equals to 100m in use case 2. The CDF of UnOv paradigm can be divided into three parts: i) the lower part (below 10 b/s/Hz) which is due to using Un paradigm for the stationary $\mathrm{UE_D}$ pair (while the other $\mathrm{UE_D}$ pair is not communicating in region $REG_{1D\&C}$); ii) the upper part (above 14 b/s/Hz) which is identical to the CDF of Un paradigm due to using this scheme for both $\mathrm{UE_D}$ pairs at the cell edge (region $REG_{D\&C}$); iii) middle part (between 10 and 14 b/s/Hz) in which the stationary $\mathrm{UE_D}$ pair uses the Un paradigm, while the other $\mathrm{UE_D}$ pair uses the Ov in this region ($REG_{D\&C}$).

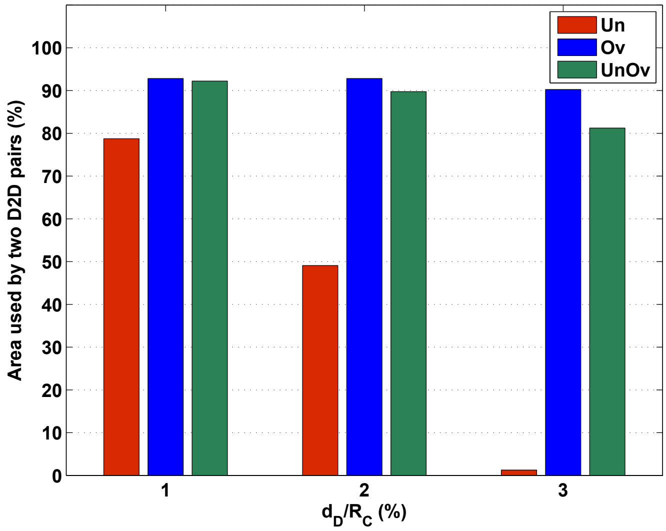

Figure 3.8: Comparison between the area used by two $\mathrm{UE_D}$ pairs in the cell using Un, Ov and UnOv over different d_D in use case 2

Figure 3.8 shows the area of $REG_{D\&C}$ using different access paradigms within different d_D in use case 2. Although the Ov paradigm outperforms both the Un and UnOv paradigms in the area of $REG_{D\&C}$ in the cell, the UnOv paradigm achieves area of $REG_{D\&C}$ close to Ov and outperforms Un paradigm.

3.5.2 Impact of Cellular SINR and Interference Margin

Applying different access paradigms makes the D2D communication restricted to the performance of cellular system which is represented by Γ_C and k. These parameters have impacts on the η_D, η_C and η_{total}. However, the impacts vary according to the geographical positions of cellular entities and the $\mathrm{UE_D}$s in the cell.

3.5.2.1 Use Case 1: SRSP

To study the impacts of Γ_C and k of cellular system on the η_{total} in use case 1 by using different access paradigms, two different positions of $\mathrm{UE_D}$ pair have been studied: i) $\mathrm{UE_D}$ pair at cell edge, as shown in Fig. 3.9 (a), and ii) $\mathrm{UE_D}$ pair at cell center, as shown in Fig. 3.9 (b). In both positions, the $\mathrm{UE_D}$ pairs use d_D/R_C of 1%.

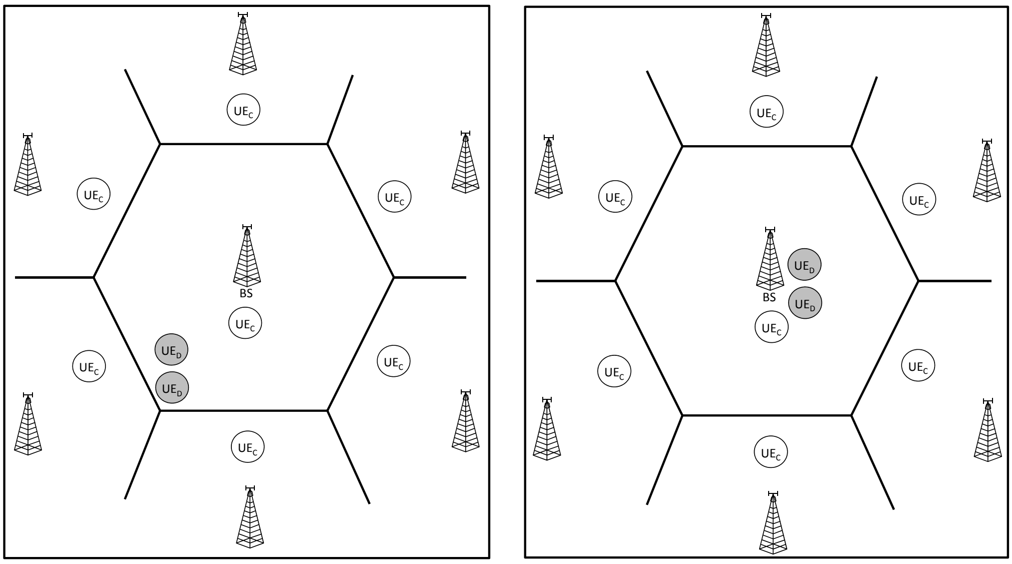

Figure 3.9: Different positions of UE_D in the cell: (a) cell edge, (b) cell center

Impact of SINR

In general, the increment in Γ_C degrades η_D while it improves the η_C. Thus, the η_{total} is stable because the improvement in η_C complement the degradation of η_D. However, the influence of Γ_C is different according to the position of UE_D pairs and the UE_C , as well as the applied access paradigm.

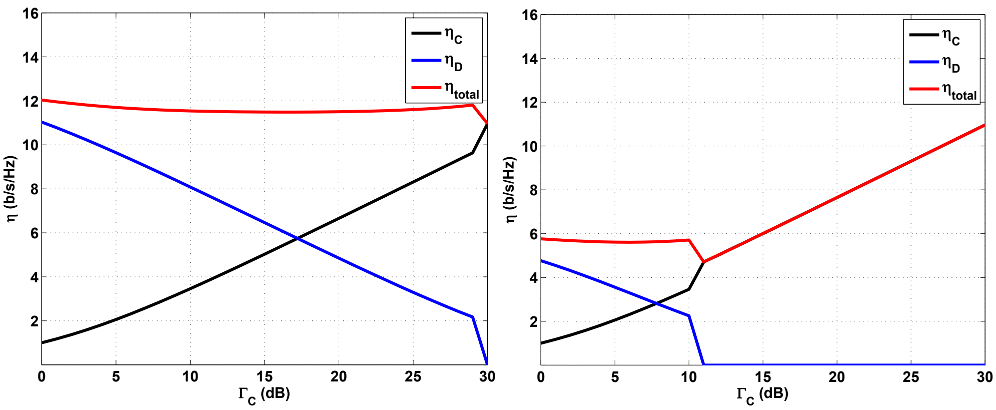

Figure 3.10: The impact of Γ_C on η_C, η_D and η_{total} using Un paradigm in use case 1 at: (a) cell edge; (b) cell center

By using Un paradigm at the cell edge, the η_{total} becomes stable within high value for wide range of Γ_C (0 to 30 dB) due to high d_{DC}^{γ} and high P_{Dmax}, as shown in Fig.

3.10 (a). However, the η_{total} is degraded by %50 at the cell center and becomes equal to η_C at low value of Γ_C (around 10 dB) due to low d_{DC}^{γ} and low P_{Dmax}, as shown in Fig. 3.10 (b).

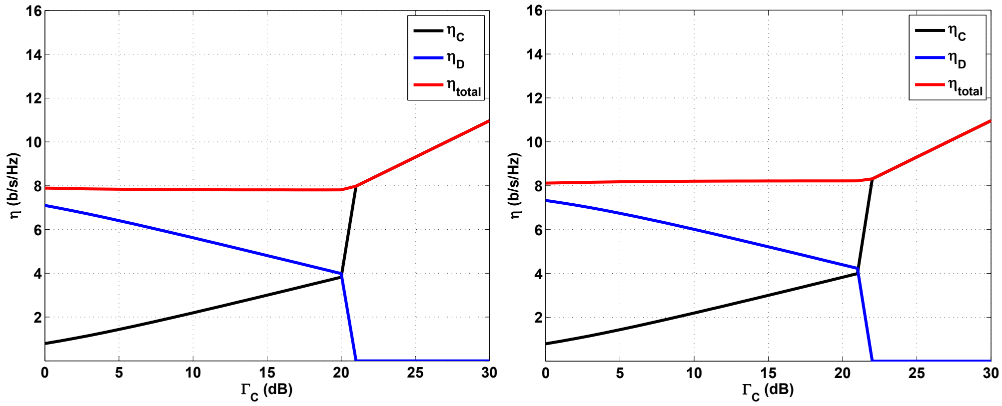

Figure 3.11: The impact of Γ_C on η_C, η_D and η_{total} using Ov paradigm in use case 1 at: (a) cell edge; (b) cell center

However, using Ov paradigm achieves a stable η_{total} at both edge and center of the cell for a wide range of Γ_C (0 to 21 dB) due to the orthogonal usage of RB between the $\mathrm{UE_C}$ and $\mathrm{UE_D}$ pair (neither intra-cell interference nor limitation in P_D from the CoI), as shown in Fig. 3.11 (a) and (b). At Γ_C of 21 dB the Γ can not be met due to high inter-cell interference which turns-off the D2D communication.

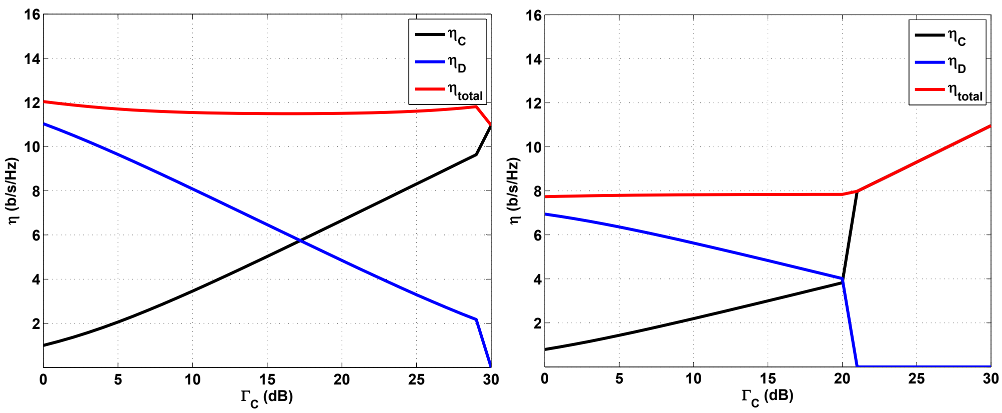

Figure 3.12: The impact of Γ_C on η_C, η_D and η_{total} using UnOv paradigm in use case 1 at: (a) cell edge; (b) cell center

Applying UnOv access paradigm achieves the best η_D at both cell edge and cell center, due to selecting the proper access paradigm according to the position of $\mathrm{UE_D}$ pair in the

CoI, as shown in Fig. 3.12 (a) and (b). Thus, the η_{total} has the best values.

Impact of Interference Margin

The k has impacts on the η_D, η_C and η_t at cell edge and cell center using different access paradigms in use case 1. In general, the k allows the $\mathrm{UE_D}$s to perform D2D communication due to the path loss from the BS which allows the $\mathrm{UE_D}$ to increase its P_D according to Eq. 3.4. Thus, the achievable Γ is increase which improves η_D and η_{total}

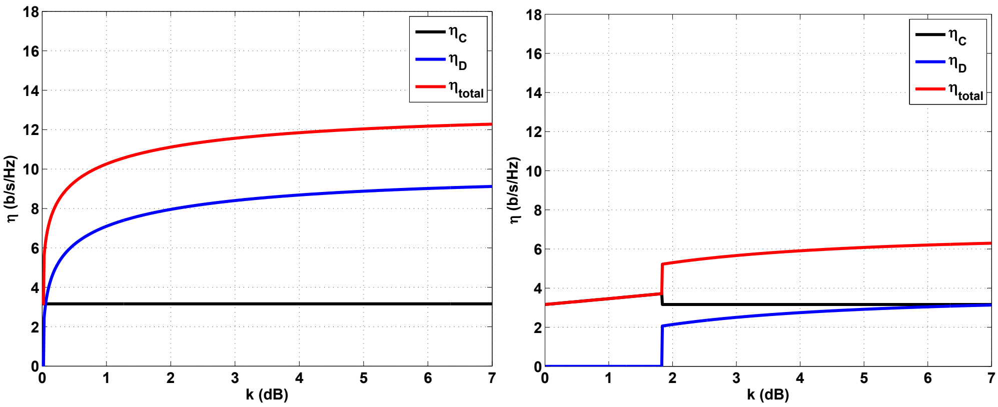

Figure 3.13: The impact of k on η_D, η_C and η_{total} using Un paradigm in use case 1 at: (a) cell edge, (b) cell center

By using Un access paradigm at the cell edge, the η_C stays fixed because any small amount of k is useful for $\mathrm{UE_D}$ pair to perform D2D communication due to the high d_{DC}^{γ} between the $\mathrm{UE_D}$ pair and the BS. Thus, any increment in K increases the P_C, as well as the interference from $\mathrm{UE_D}$ pair which makes a stable η_C, as shown in Fig. 3.13 (a). However, the small value of k has no impact on the η_D (but low impact on the η_{total}) using Un paradigm at the cell center due to the low d_{DC}^{γ} between the $\mathrm{UE_D}$ pair and the BS which may not achieve Γ_D of the D2D communication. Thus, the η_C becomes equal to η_{total} until the k becomes enough to perform D2D communication ($\Gamma \geq \Gamma_D$), as shown in Fig. 3.13 (b).

By using Ov access paradigm, the k has similar positive impact on the η_D and η_{total} at both positions (cell edge and cell center) due to orthogonal usage of the RB (in frequency dimension) with the $\mathrm{UE_C}$ in CoI. The impact of $\mathrm{UE_D}$ pair's position in the CoI on the η_D and η_{total} is only related to the d_{DC}^{γ} from the BS and d_{CD}^{γ} from the $\mathrm{UE_C}$ in the neighbor cell which defines the upper limit of P_D and the inter-cell interference, respectively, as shown in Fig. 3.14 (a) and (b).

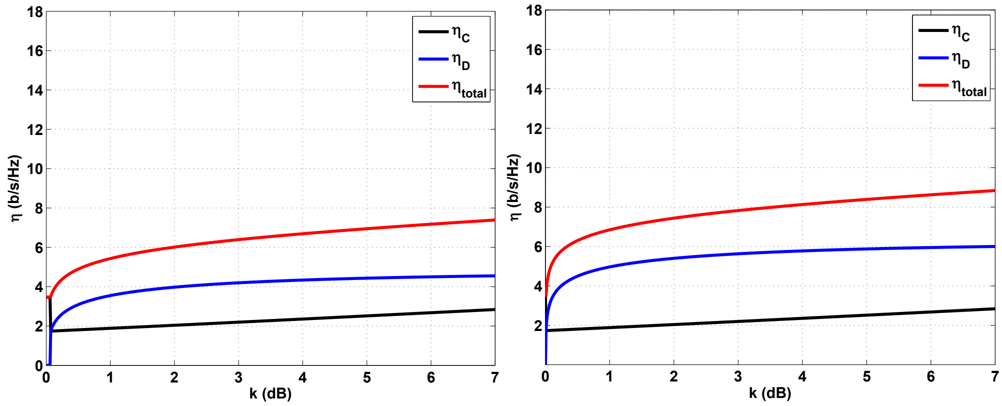

Figure 3.14: The impact of k on η_D, η_C and η_{total} using Ov paradigm in use case 1 at: (a) cell edge, (b) cell center

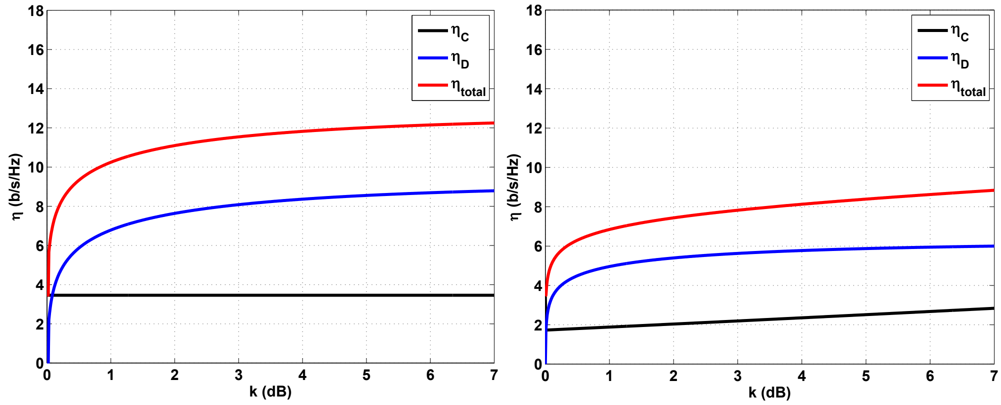

Figure 3.15: The impact of k on η_D, η_C and η_{total} using UnOv paradigm in use case 1 at: (a) cell edge, (b) cell center

Applying UnOv access paradigm improves the impact of k on the η_D and η_{total} at both edge and center of the cell due to the selection of proper access paradigm according to the position of $\mathrm{UE_D}$ pair. By applying the UnOv, the variance of η_{total} at different positions will not exceed %25 of the maximum value in the CoI (12 b/s/Hz), as shown in Fig. 3.15 (a) and (b).

3.5.2.2 Use Case 2: SRMP

To study the impacts of Γ_C and k of cellular system on the η_{total} in use case 2, two different positions of $\mathrm{UE_D}$ pair 2 have been studied: i) at cell edge, as shown in Fig. 3.16 (a), and ii) at cell center, as shown in Fig. 3.16 (b). In both positions, the both

UE_D pairs use d_D/R_C of 1%.

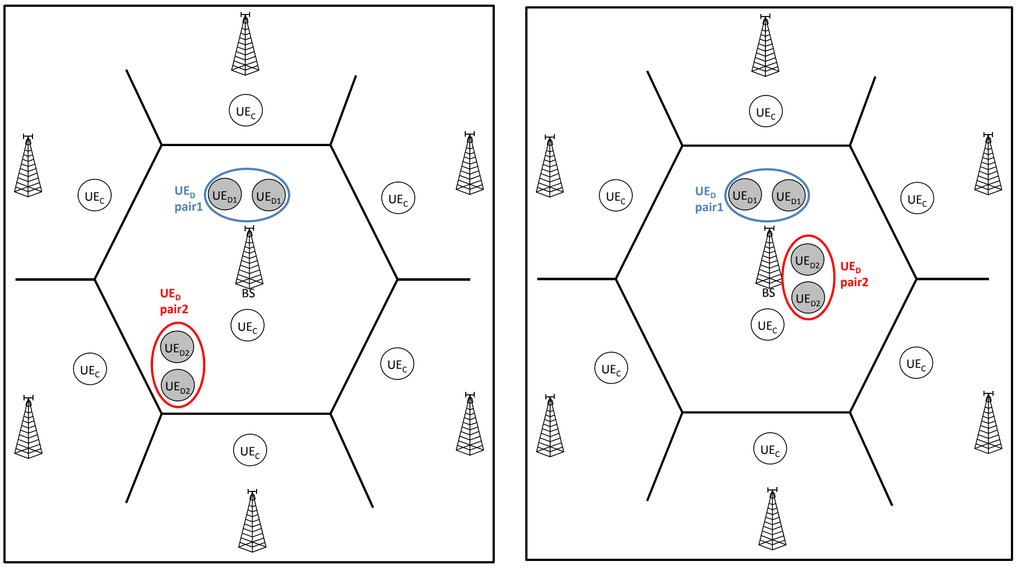

Figure 3.16: Different positions of movable UE_D pair in use case 2 at: (a) cell edge, (b) cell center

Impact of SINR

In general, the increment in Γ_C degrades the spectral efficiency of both UE_D pairs (η_{D1} and η_{D2}) which degrade η_{total}. However, the influence of Γ_C on η_{total} is different according to the position of UE_D pairs and the UE_C , as well as applied the access paradigm to perform D2D communication.

Using Un access paradigm in use case two makes both UE_D pairs share RB using Un paradigm in order not make a harmful interference at BS, according to Eq. 3.38. When the UE_D pair 2 is at the cell edge, the increment in Γ_C dramatically decreases η_{D1} and η_{D2} in spite of the improvement in the η_C because both of the UE_D pairs are far from the cellular entities and from each other, as shown in Fig. 3.17 (a). On the other hand, placing UE_D pair 2 at the cell center reduces η_{D1} and η_{D2} which reduce η_{total} in similar manner to cell edge. However, when the UE_D pair 2 is unable to perform D2D communication ($\Gamma < \Gamma_{th}$), the η_{D1} is improved due to the full usage of k value by UE_D pair 1. However, the η_{total} has a degradation due to the loss of η_{D2} and becomes stable while UE_D pair 1 performs D2D communication which is similar to use case 1, as shown in Fig. 3.17 (b).

By using Ov access paradigm by both UE_D pairs, η_{D1}, η_{D2}, and η_{total} have slightly

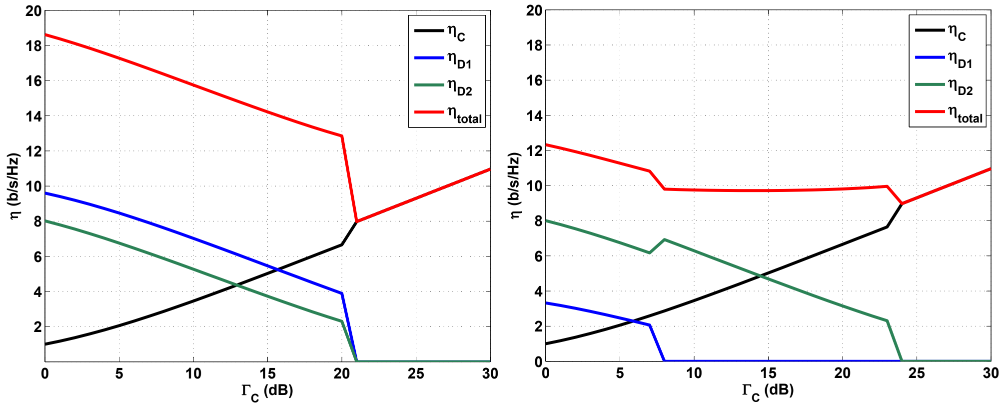

Figure 3.17: The impact of Γ_C on $\eta_D 1$, $\eta_D 2$, η_C and η_{total} using Un paradigm in use case 2 at: (a) cell edge, (b) cell center

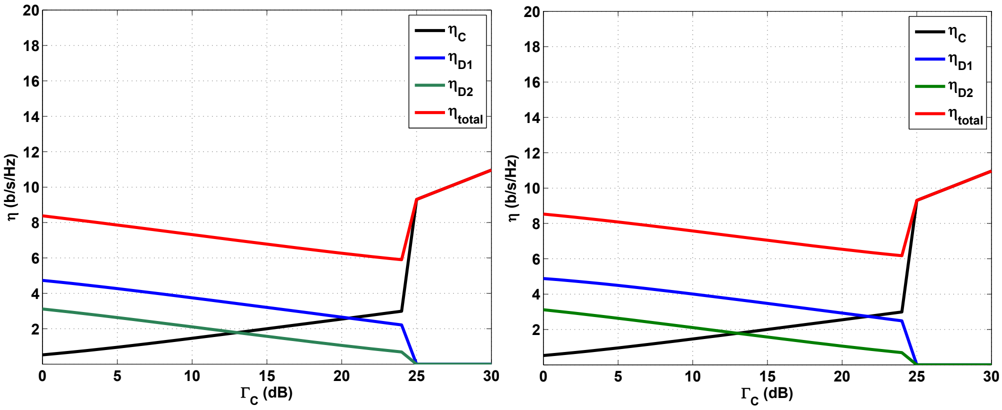

Figure 3.18: The impact of Γ_C on η_{D1}, η_{D2}, η_C and η_{total} using Ov paradigm in use case 2 when $\mathrm{UE_D}$ pair 2 is at: (a) cell edge, (b) cell center

change with the increment of Γ_C due to the orthogonal use of RB in COI. Thus, $\mathrm{UE_D}$ pairs are affected only by the inter-cell interference at different positions in the COI, as shown in Fig. 3.18 (a) and (b).

Applying UnOv in use case 2 improves the η_{total} at different positions in the cell due to selecting the proper access paradigm for each $\mathrm{UE_D}$ pair to achieve the maximum η_{total} using Un paradigm for both $\mathrm{UE_{D1}}$ pair and $\mathrm{UE_{D2}}$ pair. At the cell edge, increasing the Γ_C to a higher value makes the Un access paradigm unsuitable for both $\mathrm{UE_D}$ pairs due to achievable Γ of them. In such a case, the BS sets Ov access paradigm for $\mathrm{UE_{D1}}$ while keeps $\mathrm{UE_{D2}}$ using Un paradigm. As a consequence of setting Ov paradigm for $\mathrm{UE_{D1}}$, 50% of the RB is dedicated for it which reduces the amount of RB allocated for $\mathrm{UE_C}$ by 50%. Thus, the η_C is degraded by 41% while the η_{total} is decreased by only 15% due to

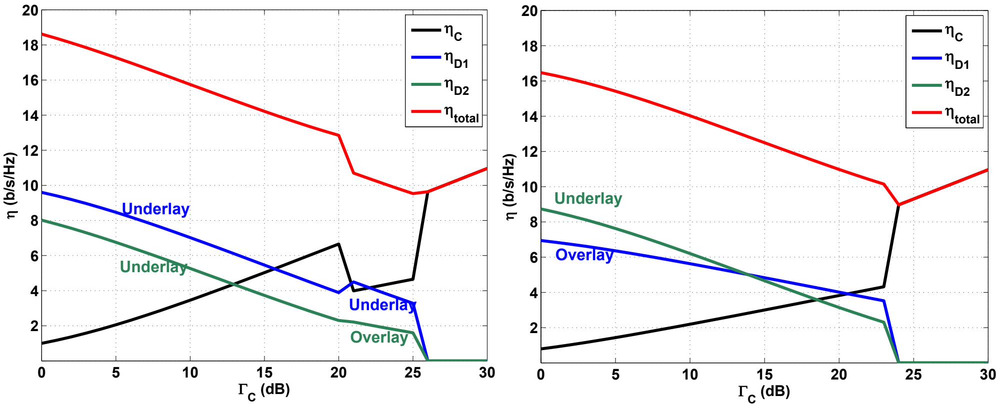

Figure 3.19: The impact of Γ_C on η_{D1}, η_{D2}, η_C and η_{total} using UnOv paradigm in use case 2 when $\mathrm{UE_D}$ pair 2 is at: (a) cell edge, (b) cell center

the improvement of η_{D1}, as shown in Fig. 3.19 (a). At the cell center, the BS decides to set different access paradigms for the $\mathrm{UE_D}$ pairs within low Γ_C to achieve higher η_{D1}, η_{D2} and η_{total} as shown in Fig. 3.19 (b).

Impact of Interference Margin

The k has impacts on the η_{D1}, η_{D2}, η_C and η_{total} when the $\mathrm{UE_D}$ pair 2 is at cell edge and cell center using different access paradigms in use case 2. In general, the k allows the $\mathrm{UE_D}$ pairs to perform D2D communication due to the distance from the BS which allows the $\mathrm{UE_D}$ to increase P_D according to Eq. 3.4. Thus, the achievable Γ is increase which improves η_{D1} and η_{D2}, as well as η_{total}

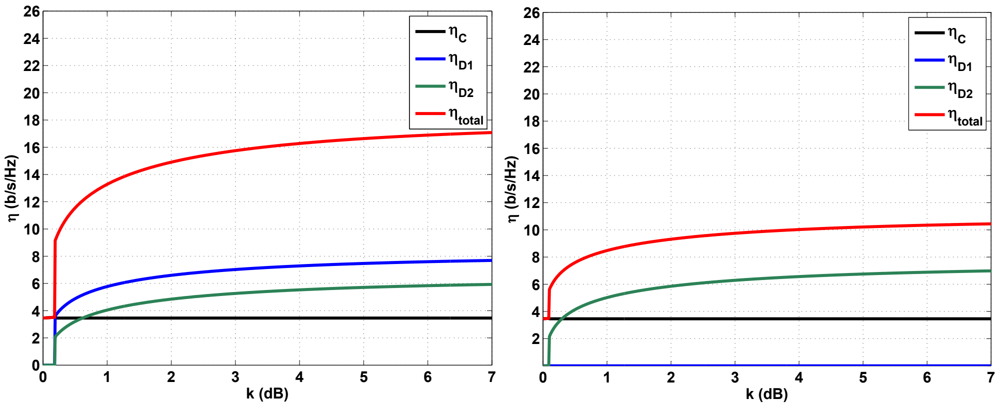

Figure 3.20: The impact of k on η_{D1}, η_{D2}, η_C, and η_{total} using Un access paradigm in use case 2 when $\mathrm{UE_D}$ pair 2 is at: (a) cell edge, (b) cell center

By using Un access paradigm at the cell edge, k has a positive impact on the η_{D1}, η_{D2} and η_{total} due to the far distance from the $\mathrm{UE_D}$ pair and the BS which achieves high η_{total}, as shown in Fig. 3.13 (a). However, k has no impact on the η_{D2} using Un paradigm at the cell center due to the short distance between the $\mathrm{UE_D}$ pairs and the BS which may not achieve Γ_{th} of the D2D communication, as shown in Fig. 3.13 (b).

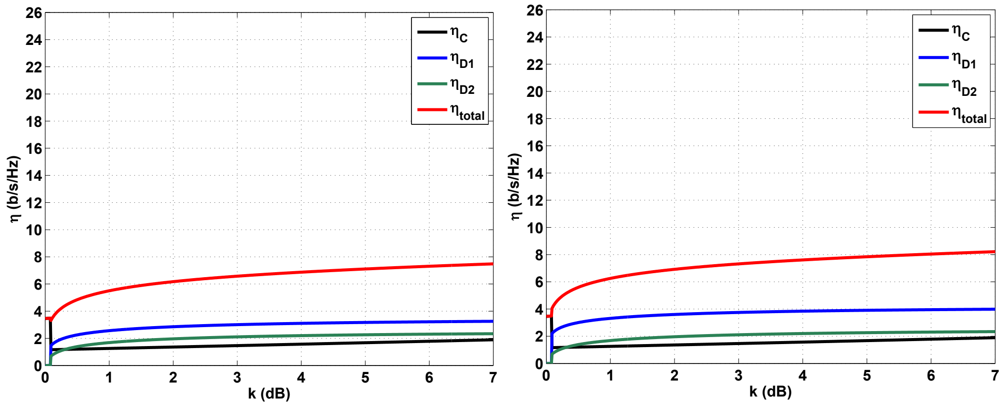

Figure 3.21: The impact of k on η_{D1}, η_{D2}, η_C, and η_{total} using Ov access paradigm in use case 2 when $\mathrm{UE_D}$ pair 2 is at: (a) cell edge, (b) cell center

By using Ov access paradigm for both $\mathrm{UE_D}$ pairs, the k has similar positive impact on the η_D and η_{total} at over the cell due to orthogonal usage of the RB with the $\mathrm{UE_C}$ in CoI. The impact of $\mathrm{UE_D}$ pair's position in the cell on the η_{D1}, η_{D2} and η_{total} is only related to the distance from the BS in the neighbor cell which defines the upper limit of P_D, as shown in Fig. 3.14 (a) and (b).

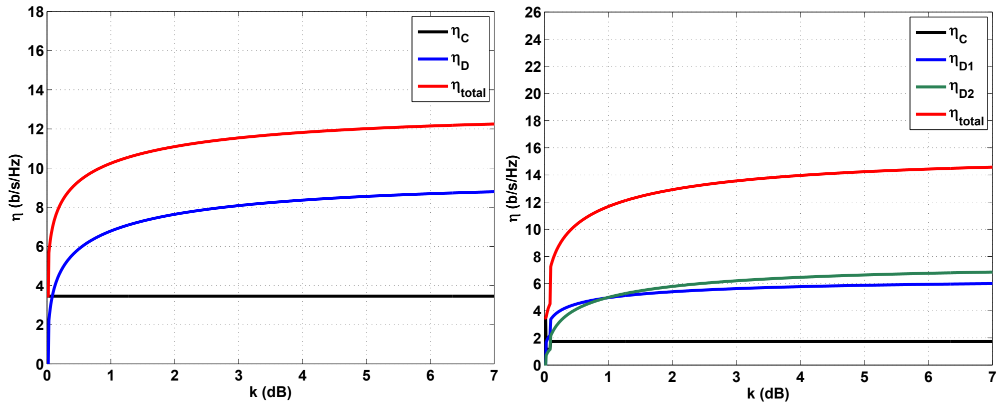

Figure 3.22: The impact of k on η_{D1}, η_{D2}, η_C, and η_{total} using UnOv access paradigm in use case 2 when $\mathrm{UE_D}$ pair 2 is at: (a) cell edge, (b) cell center

Applying UnOv access paradigm improves the impact of k on the η_{D1}, η_{D2} and η_{total} at both edge and center of the cell due to the selection of proper access paradigm according to the position of each $\mathrm{UE_D}$ pair. At the cell edge, each $\mathrm{UE_D}$ pair is using Un access paradigm. While at the cell center, the $\mathrm{UE_D}$ pair 2 uses Ov access paradigm in order to improve η_{total}. By applying the UnOv, the variance of η_{total} at different positions will not exceed %25 of the maximum value in the CoI (12 b/s/Hz), as shown in Fig. 3.22 (a) and (b).

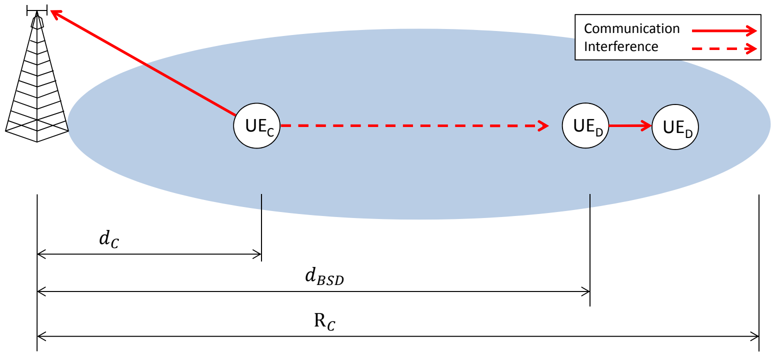

Figure 3.23: Simulation scenario

3.5.3 Impact of Geographical Positions of $\mathrm{UE_C}$ and $\mathrm{UE_D}$ pair

The geographical positions of cellular entities and the $\mathrm{UE_D}$ have an impact on the D2D communication performance [KA08, KLA13]. The geographical positions of the entities (BS, $\mathrm{UE_C}$s and $\mathrm{UE_D}$s) make different path losses between the entities themselves, which have positive and negative impacts on the η_{total} according to the position of the entities. Figure 3.23 shows the scenario of different positions of $\mathrm{UE_C}$ and $\mathrm{UE_D}$ pair in the cell, which are in line of sight with the BS.

Figures 3.24 (a), (b) and (c) show the impacts of geographical position of $\mathrm{UE_C}$ (d_C) and $\mathrm{UE_D}$ (the distance between $\mathrm{UE_D}$ and BS d_{BSD}) in the cell using Un, Ov and UnOv paradigms, respectively. The UnOv paradigm outperform both Un and Ov paradigms over the cell due to applying the Ov paradigm close to $\mathrm{UE_C}$ and in between BS and $\mathrm{UE_C}$, while it applies Un at positions far from the BS and $\mathrm{UE_C}$ which achieves the highest η_{total}.

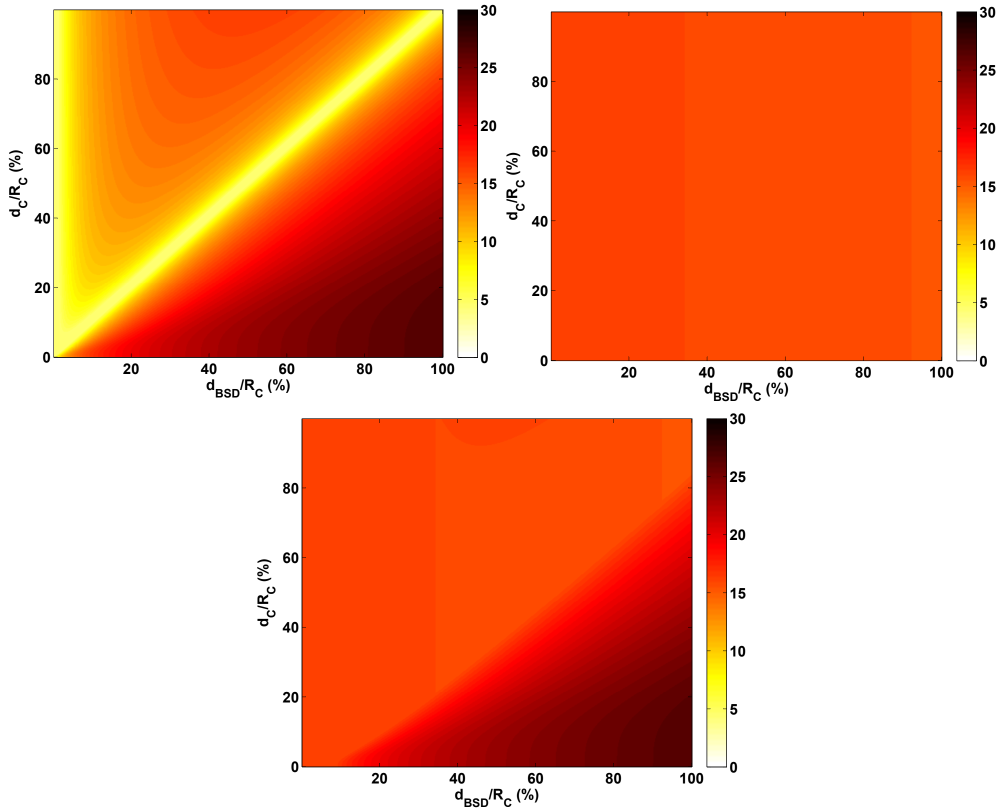

Figure 3.24: The relation between d_C and d_{BSD} in the cell using: (a) Un paradigm; (b) Ov paradigm; (c) and UnOv paradigm

3.5.4 Impact of Multiple D2D Communication in the Cell

Introducing multiple D2D communications by reusing the RB with the cellular system has positive and negative impacts on η_{total} in the cell. The positive impact is increasing the number of active $\mathrm{UE_D}$ pairs in the cell which rises the η_{total}. However, this has a negative impact on the intra-cell interference between the $\mathrm{UE_D}$ pairs which reduces the Γ of the D2D communications (using the Un access paradigm), as well as the reducing the dedicated RB's portion for both D2D communications and the cellular communication (using the Ov access paradigm) which decreases η_C, η_D and η_{total}, according to Eq. 3.58.

Figures 3.25 (a) and (b) show the η_{total} in presence of multiple $\mathrm{UE_D}$ pairs using different access paradigm with a d_D/R_C of 0.5% and 1%, respectively. In general, the UnOv access paradigm outperforms both Un and Ov access paradigms due to set different access paradigm to $\mathrm{UE_D}$ pairs to increase the D2D communications and improve the η_{total}. The UnOv paradigm keeps outperforming the Ov paradigm until no D2D communication

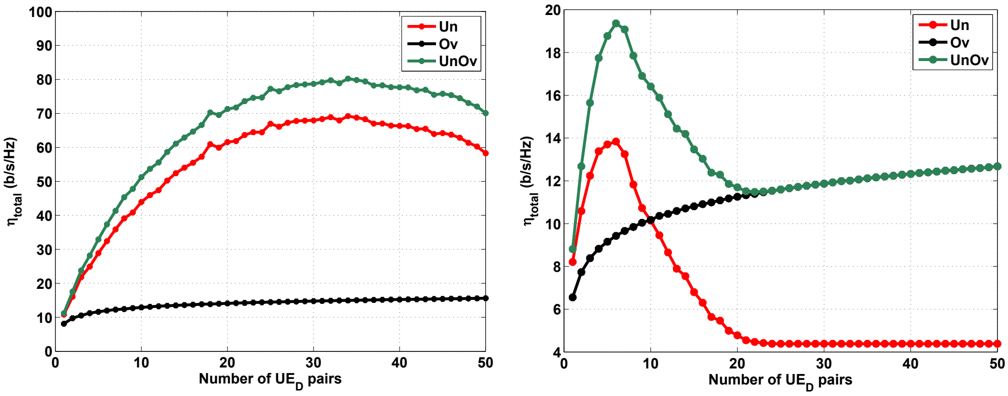

Figure 3.25: The relation between η_{total} and the number of UE_D pairs in the cell using: (a) d_D/R_C=0.5%; (b) d_D/R_C=1%

using Un access paradigm can be performed. At this point, the UnOv paradigm becomes identical with the Ov paradigm.

The increment in the number of UE_D pairs increases the η_{total} till a certain number of UE_D pairs which achieve the maximum η_{total}. However, increasing the number of UE_D pairs increases the intra-cell interference which degrades the Γ of UE_D pairs (which use the Un paradigm) below the Γ_D and become unable to perform D2D communication using Un paradigm. In such a case, the UnOv sets Ov paradigm for all the UE_D pairs in the cell. The maximum value of η_{total} represents the maximum number of the UE_D pairs (using Un and Ov paradigms) which can reuse the RB with the cellular system.

The behavior of η_{total} using Un and UnOv access paradigms depends on d_D which has influence on number of UE_D pairs which achieves the maximum η_{total}, as well the maximum value of η_{total} itself, as shown in Fig. 3.25 (a) and (b).

Figures 3.26 (a) and (b) show the percentage of satisfied UE_D pairs ($\Gamma \geq \Gamma_D$)in the cell using different access paradigms with d_D of 50m and 100m, respectively. By using Un paradigm, the number of satisfied UE_D pairs drastically decreases by adding more pairs due to increase of intra-cell interference which degrade Γ below the threshold. Another factor which influences the percentage of satisfied UE_D pairs is influenced by the d_D which changes the degradation behavior from semi-linear, as in Fig. 3.26 (a), to semi-exponential, as in Fig. 3.26 (b), by increasing the d_D from 50m to 100m, respectively.The Ov and UnOv access paradigms have no degradation in the percentage of satisfied UE_D pairs, compared to Un paradigm, due to set Ov access paradigm to the UE_D pairs.

To quantify the η_{total} in the cell, area spectral efficiency ASE is introduced as a meter of spectral efficiency per unit area in the cell [AG99, ZYH13, STA14]. In the dissertation,

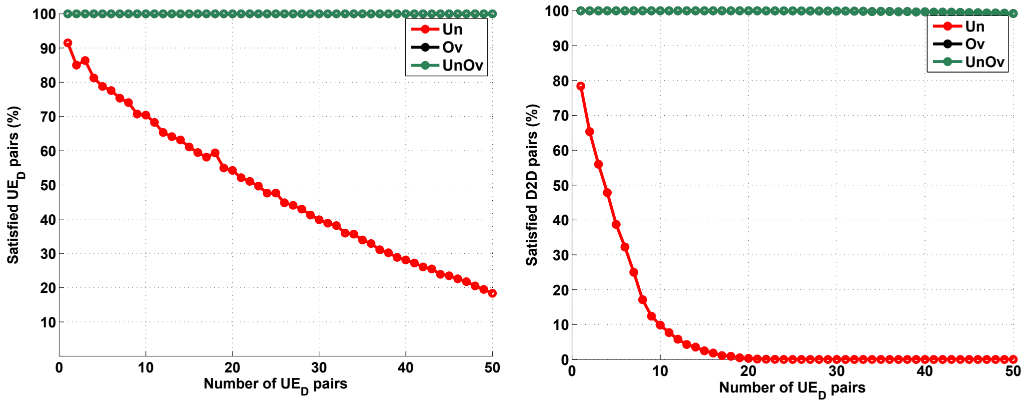

Figure 3.26: The percentage of satisfied UE$_\mathrm{D}$ pairs in the cell using: (a) d_D=50m; (b) d_D=100m

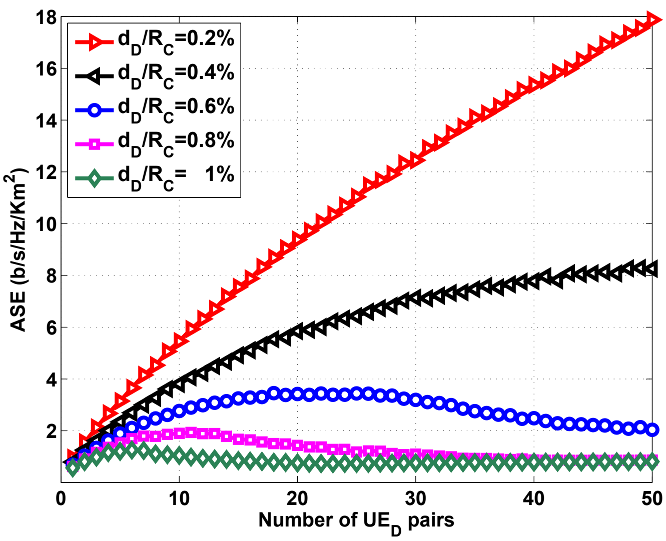

Figure 3.27: ASE vs. different d_D values

the ASE is introduced as the total spectral efficiency η_{total} (of UE$_\mathrm{C}$ and UE$_\mathrm{D}$ pairs in CoI which use the same RB) per unit area ($b/s/Hz/Km^2$). Figure 3.27 shows the behavior of ASE with the increase of number of UE$_\mathrm{D}$ pairs in the cell using different d_D. The increase of d_D/R_C has a negative influence on the ASE due to the increase the spatial of intra-cell interference in the cell. Thus, the increase of d_D/R_C pushes the maximum value of η_{total} down toward low number of UE$_\mathrm{D}$ pairs which defines the best number of UE$_\mathrm{D}$ pairs in the cell.

3.6 Summary

The $\mathrm{UE_D}$ pairs perform D2D communications using two different access paradigms. By using Un paradigm, any $\mathrm{UE_D}$ pair shares the RBs with the cellular system without making a harmful interference with the cellular entities (BS in UL and $\mathrm{UE_C}$ in DL). The drawbacks of Un paradigm are: i) intra-cell interference from cellular entities and other $\mathrm{UE_D}$ pairs; ii) limitation in P_D; iii) limited positions in the cell in which the D2D communication is performed; and iv) limited number of satisfied $\mathrm{UE_D}$ pairs. By using Ov paradigm, the $\mathrm{UE_D}$ uses a dedicated portion of RBs (in frequency domain) to perform the D2D communication. So, the $\mathrm{UE_D}$ adapts its upper limit of P_D according to the closest C-Rx in the neighbor cells. Thus, by using Ov access paradigm the P_D will be high, compared to Un paradigm, which makes Γ high, compared to Un paradigm. However, the drawbacks of Ov paradigm are: i) low η_{total} achieved, compared to Un paradigm, due to the partial usage of RB by both $\mathrm{UE_D}$ pairs and the $\mathrm{UE_C}$; ii) joint scheduling is required at BS to perform orthogonal usage of RB; iii) low improvement in η_{total} by increasing the number of $\mathrm{UE_D}$ pairs.

To conquer the aforementioned drawbacks, a hybrid access paradigms is proposed in this chapter which utilizes the RB in frequency. The proposed paradigm is a merge of Un and Ov access paradigm which called UnOv paradigm. This access paradigm considers either using the whole RB with low power (Un), or dividing the RB in frequency dimension between the $\mathrm{UE_D}$ pair and the $\mathrm{UE_C}$ (Ov). By using this paradigm, the BS selects the proper access paradigm for each $\mathrm{UE_D}$ pair according to the geographical positions of $\mathrm{UE_D}$ pairs and the $\mathrm{UE_C}$, as well as the QoS requirements in CoI and the neighbor cells.

To study the performance of the proposed access paradigm, different use cases have been discussed which show the η_{total} at presence of single and multiple $\mathrm{UE_D}$ pairs in the CoI.

Integrating D2D communication with the cellular systems improves the total spectral efficiency and increase the number of served licensed users with less signaling through the BS. However, the cellular systems still have some issues related to the low spectrum utilization due to the presence of spectrum holes which are not utilized (low users activities). On the other hand, some unlicensed users have problem of unavailable free spectrum to access due to high number of unlicensed users, compared to number of free spectrum bands.

4 Analytical Model of System Capacity for UD2D Communication

Contents

Performing communication of unlicensed users over licensed spectrum band has been proposed by many researcher to improve the spectrum utilization and the spectral efficiency of the licensed spectrum. Such proposed idea is connected to the usage of CR technique in order to perform opportunistic spectrum access, in which no interference is allowed with the licensed users. Avoiding interference with cellular system, i.e. PUs, is the main constraint which influences the communication of the unlicensed users, i.e. SUs.

This chapter introduces a detailed study of using CR technology in the cell to integrate SU communication with cellular system. The SU can perform direct communication which is similar to D2D communication. However, no degradation is allowed in the performance of cellular system. Thus, the SU communication can be called Unlicensed D2D (UD2D) communication which consists of unlicensed user equipments ($\mathrm{UE_D}$s). By applying CR technology in $\mathrm{UE_D}$, the UD2D communication is performed in cellular band using access paradigms. The spectral efficiency of UD2D communication is studied using each access paradigm to have a clear view about the strong and the weak points by each one. Then, a new access paradigm is presented to overcome the drawbacks of the predefined the access paradigms. Later, an enumeration has been applied to evaluate the spectral efficiency of UD2D communication in the proposed access paradigm.

This chapter is organized as follows: the system model is described in details. The CR access paradigms are studied and the system spectral efficiency is determined by each one. Then, a new access paradigm is introduced and detailed study of system spectral efficiency is presented. Later, numerical simulations have been performed to evaluate performance UD2D communication using different access paradigms.

4.1 System Model of UD2D Communication

The system model in this chapter is similar the system model in Section 3.1, as shown in Fig. 3.1. The cellular network consists of 7 neighbor macro cells of a radius R_C with a frequency reuse factor of 1. Each cell consists of a BS and a number of $\mathrm{UE_C}$s distributed in the cell. The BS is equipped with omnidirectional antenna and its spectrum band is divided into UL and DL sub-bands using FDD scheme. Each sub-band is divided into number of channels with frequency f_c which is divided using TDMA to generate RBs.

In addition to the $\mathrm{UE_C}$s, there is $\mathrm{UE_D}$ pair which attempts to achieve direct communication using UL band of the cellular system. Each $\mathrm{UE_D}$ is equipped with CR technology to perform cognitive communication. The $\mathrm{UE_D}$ uses wide band spectrum sensing to detect the activities of cellular entities efficiently. The $\mathrm{UE_D}$ senses the pilot signal of BS to estimate the distance to the BS d_{BSU}. Also, it determines Γ_C of the cellular system and BS sensitivity SS_{BS} from the BS pilot signal.

4.2 Cognitive Radio Access Paradigms

Performing UD2D communication using CR technology requires using access paradigms which manage the operation of CR over the cellular band. The performance of access paradigms in CR have some similar behavior in D2D communication. However, the main constraint is avoiding harmful interference at the cellular users.

In the next subsections, the access paradigms of CR are explained.

4.2.1 Underlay

Performing underlay (Un) access paradigm using CR technology has similar behavior to D2D communication which should not generate a harmful interference at BS, as explained in Section 3.2.1.

4.2.2 Interweave

Interweave (Iw) access paradigm is based on Opportunistic Spectrum Access (OSA) in which each UE_D pair exploits the spectrum orthogonally in time-space-frequency dimensions relative to UE_C signal [BGG+12]. This paradigm requires a perfect detection of UE_C activities on both UE_D-Tx and UE_D-Rx sides in order to find the common spectrum holes (at the same time and frequency dimensions on both sides). The sensed activities of UE_Cs over the sub-channels are changed over time and depend on their geographical position in the cell, which require efficient sensing schemes to have a perfect detection.

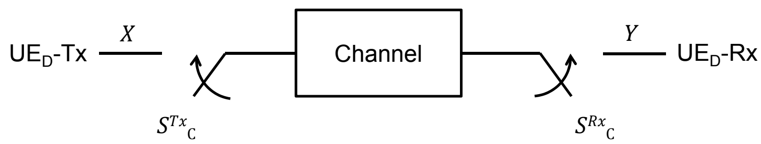

Figure 4.1: Switch model [JS07]

According to [JS07], the Iw paradigm is applied in UE_D pair using random switch model for the spectrum holes using perfect sensing of spectrum band, as shown in Fig. 4.1. In this model, S_C^{Tx} and $S_C^{Rx} \in \{0, 1\}$ are binary variables which represent the states of the switch at both sides of UE_D. The switch is OFF ($S_C = 0$) when UE_C activity is detected, and vice versa. Both sides of UE_D pair sense the spectrum band for time interval [0, T] to find the amount of time the switches (on both sides) being ON and OFF, T_{ON} and T_{OFF}, respectively. The fraction of time the UE_Ds can not access the spectrum band is $\frac{T_{OFF}}{T}$, which can be formulated for stationary and ergodic UE_C as the probability of UE_C being ON ψ_C (switch is open). Thus, the relation between the transmitted signal X and the received signal Y is:

$$Y = S_C^{Rx}(S_C^{Tx} X + \sigma_n^2) \tag{4.1}$$

The P_D in this scheme has a lower bound of:

$$P_D \geq \Gamma_D d_D^{\gamma} \sigma_n^2 \tag{4.2}$$

The probability of UD2D communication using Iw paradigm $P^{Iw}(D)$ is 1-ψ_C, and the spectral efficiency of UD2D communication using Iw paradigm η_D^{Iw} is [JS07]:

$$\eta_D^{Iw} = (1-\psi_C^{Tx})(1-\psi_C^{Rx})\log_2\left(1+\frac{\Gamma_D d_D^{\gamma}\sigma_n^2}{(1-\psi_C^{Tx})\sigma_n^2}\right), \tag{4.3}$$

where ψ_C^{Tx} and ψ_C^{Rx} are the probability of $\mathrm{UE_C}$ being ON at $\mathrm{UE_D}$-Tx and $\mathrm{UE_D}$-Rx, respectively.

The cellular spectral efficiency using Iw paradigm η_C^{Iw} is:

$$\eta_C^{Iw} = \psi_C \log_2\left(1+k\Gamma_C\right) \tag{4.4}$$

Thus, the total spectral efficiency in the cell using Iw η_{total}^{Iw} is:

$$\eta_{total}^{Iw} = \eta_C^{Iw} + \eta_D^{Iw} \tag{4.5}$$

4.3 Integrating Underlay and Interweave Access Paradigms

Although applying CR technology using Un outperforms the Iw paradigms in improving η_D and η_{total} over the cell with full RB utilization, the performance of $\mathrm{UE_D}$s (η_D) is still limited due to: i) high interference generated by the close to $\mathrm{UE_C}$; ii) low P_{Dmax} which limits the performance, especially if the $\mathrm{UE_D}$-Tx is close to BS; and iii) the high d_D^{γ} which has a negative impact on the achievable Γ at some positions in the cell. Thus, some positions in the macro cell have no possible UD2D communication ($\Gamma < \Gamma_D$) simultaneously with the cellular system.

In addition to the aforementioned limitations, the resource utilization by the conventional cellular communication is low. According to exhaustive measurements campaigns in [ALVM06], the activity of cellular entities over cellular band varies over time (15% to 85%) depending on the activity of the $\mathrm{UE_C}$s. This leads to many spectrum holes in space-time-frequency dimensions of the spectrum band which are not utilized in the cell. Thus, a degradation occurs in η_{total} of the cell.

To improve the spectrum utilization, there is a need to define:

- The interference generated from $\mathrm{UE_C}$s to $\mathrm{UE_D}$ pair I_C within each RB at each position in the cell, which depends on d_{CD}.
- The activity of $\mathrm{UE_C}$s within RBs.

Each $\mathrm{UE_C}$ has an activity which can be modeled into two states of the Markov process: ON and OFF. The RB is in ON state with a probability ψ_C and in OFF state with probability $1 - \psi_C$. According to [ALVM06, ALC09, GJMS09], unlicensed user can access spectrum holes in the band without interfering the licensed user. This can be done using Iw access paradigm.

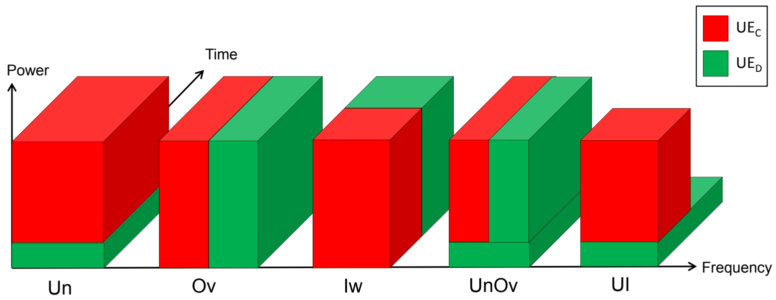

Figure 4.2: Different access paradigms

By merging the Iw and Un access paradigms, a degree of freedom is added to the UD2D communication due to: i) the use of Un paradigm which ensures no interference can occur with the C-Rx (BS) at any position in CoI, especially if any change is occurred in the cellular user's activity (sensing is not required at UE$_\mathrm{D}$-Tx); ii) the Iw paradigm which gives the possibility to perform UD2D communication at positions close to C-Tx (UE$_\mathrm{C}$ by accessing the spectrum holes (sensing is required only at UE$_\mathrm{D}$-Rx to avoid degradation in Γ due to interference from C-Tx); and iii) no need for identical spectrum holes at both sides of UE$_\mathrm{D}$ pair due to the usage of Un access paradigm which avoids interference at C-Rx (UE$_\mathrm{D}$-Tx can send its signal using any sub-channel which has spectrum holes at UE$_\mathrm{D}$-Rx). Thus, a new access paradigm called Underlay-Interweave (UI) is proposed which improves the performance of UD2D communication with no degradation in the performance of cellular system. The proposed access paradigm allows to perform UD2D communication over the full frequency dimension of RB but partially in time (the orthogonality is in time which is different from Ov paradigm) at positions close to C-Tx, while it uses only underlay at position far from UE$_\mathrm{C}$ in which the interference does not degrade the achievable Γ. Applying Un access paradigm has an advantage of avoiding any interference from UE$_\mathrm{D}$-Tx to BS due to unpredictable behavior of UE$_\mathrm{C}$ (change in ψ_C). Figure 4.2 shows the resource allocation in time and frequency dimensions using different access paradigms.

The interference generated by each UE$_\mathrm{C}$ of ψ_C activity has I_C with two discrete values $[0,\, k\Gamma_C\sigma^2(\frac{d_C}{d_{CD}})^\gamma]$. The Probability Density Function (PDF) of this interference $f_{I_C}(x)$ is:

$$f_{I_C}(x) = \psi_C\delta(x - (k\Gamma_C\sigma^2(\frac{d_C}{d_{CD}})^\gamma)) + (1-\psi_C)\delta(x), \tag{4.6}$$

where x is the interference.

The I_C is non zeros with the probability of ψ_C and is zeros with probability of 1-ψ_C.

By using UI access paradigm, the total interference measured at UE$_\mathrm{D}$-Rx I_t can be classified as: i) interference $I_t^{D\&C}$ if UE$_\mathrm{D}$ pair is a region allows performing UD2D communication simultaneously with cellular communication $REG_{D\&C}$; ii) interference $I_t^{D/C}$ if UE$_\mathrm{D}$ pair is in region allows performing UD2D communication orthogonal in time dimension relative to cellular communication $REG_{D/C}$; and iii) interference I_t^C if UE$_\mathrm{D}$ pair in a region does not allow UD2D communication REG_C. Thus, the I_t can be expressed as:

$$I_t = \begin{cases} I_t^{D\&C}, & \text{if } \frac{\left(\frac{d_{DC}}{d_D}\right)^\gamma}{\sum_{i=1}^{N_C}\left(\frac{d_{C_i}}{d_{C_iD}}\right)^\gamma} \geq \frac{k\ \Gamma_C\ \Gamma_D}{k-1} \\ I_t^{D/C}, & \text{if } \frac{\left(\frac{d_{DC}}{d_D}\right)^\gamma}{\sum_{i=1}^{N_C}\psi_{C_i}\left(\frac{d_{C_i}}{d_{C_iD}}\right)^\gamma} \geq \frac{k\ \Gamma_C\ \Gamma_D}{k-1} \\ I_t^C, & \text{if } \frac{\left(\frac{d_{DC}}{d_D}\right)^\gamma}{\sum_{i=1}^{N_C}\psi_{C_i}\left(\frac{d_{C_i}}{d_{C_iD}}\right)^\gamma} < \frac{k\ \Gamma_C\ \Gamma_D}{k-1} \end{cases} \tag{4.7}$$

In $REG_{D\&C}$, the $I_t^{D\&C}$ at UE$_\mathrm{D}$-Rx in the CoI includes the interference from all the UE$_\mathrm{C}$s (in CoI and neighbor cells). The $I_t^{D\&C}$ is defined as:

$$I_t^{D\&C} = \sum_{i=1}^{N_C} \psi_C k \Gamma_C \sigma_n^2 \Big(\frac{d_{C_i}}{d_{C_iD}}\Big)^\gamma, \tag{4.8}$$

where $d_{C_iD}^\gamma$ is the path loss between the UE$_\mathrm{D}$-Rx and the i^{th} UE$_\mathrm{C}$ (in the CoI and the neighbor cells) that utilize the same RB.

While each UE$_\mathrm{C}$ generates an interference with a PDF $f_{I_{C_i}}(x)$ which is independent and distributed according to Eq.4.6, the PDF of total interference in $REG_{D\&C}$ region $f_{I_t^{D\&C}}(x)$ is:

$$f_{I_t^{D\&C}}(x) = \mathbf{conv}\{f_{I_{C_i}(x)}\}, \tag{4.9}$$

While the $I_t^{D\&C}$ has the main external negative influence on the Γ, the probability of UD2D communication in $REG_{D\&C}$ regions $Prob(D|D\&C)$ can be represented as a CDF of the interference at UE$_{\mathrm{D}}$-Rx $F(I_t^{D\&C} \leq \frac{P_D d_D^{-\gamma}}{\Gamma_D} - \sigma_n^2)$.

By substituting Eq. 3.4, the $Pr(D|D\&C)$ can be modeled as:

$$Prob(D|D\&C) = \int_0^{I_{max}} f_{I_t^{D\&C}}(x)dx, \tag{4.10}$$

where $I_{max} = (k-1)\sigma_n^2 \ (\frac{d_{DC}}{d_D})^\gamma - \sigma_n^2$.

Thus, the spectral efficiency in $REG_{D\&C}$ regions $\eta_D^{D\&C}$ is:

$$\eta_D^{D\&C} = Prob(D|D\&C) \ E\Big\{ \log_2 \Big(1 + \frac{P_D d_D^{-\gamma}}{I_t^{D\&C} + \sigma_n^2}\Big)\Big\}, \tag{4.11}$$

Eq. 4.11 can be simplified as:

$$\eta_D^{D\&C} = Prob(D|D\&C) \int_{-\infty}^{\infty} \log_2 \left(1 + \frac{(k-1)\sigma_n^2 d_{DC}^\gamma}{x + \sigma_n^2}\right) f_{I|U}^{D\&C}(x) \ dx, \tag{4.12}$$

where $f_{I|D}^{D\&C}(x)$ is a conditional PDF of $I_t^{D\&C}$ which is:

$$f_{I|D}^{D\&C}(x) = \frac{f_{I_t^{D\&C}}(x)}{\int_0^{I_{max}} f_{I_t^{D\&C}}(x)dx}, \text{for } 0 \leq x < I_{max}$$

In $REG_{D/C}$ regions which are close to number of C-Txs (J), the UD2D communication is performed during their OFF periods. The $I_t^{D/C}$ is:

$$I_t^{D/C} = \sum_{i=1, i \notin J}^{Nc} \psi_{C_i} \ k\Gamma_C \ \sigma_n^2 (\frac{d_{C_i}}{d_{C_i D}})^\gamma, \tag{4.13}$$

The PDF of total interference in $REG_{D/C}$ regions $f_{I_t^{D/C}}$ is:

$$f_{I_t^{D/C}}(x) = \mathbf{conv}\{f_{I_{C_i}(x)}\}, \tag{4.14}$$

The probability of UD2D communication in $REG_{D/C}$ regions $Prob(D|D/C)$ is modeled as:

$$Prob(D|D/C) = \prod_{i=1}^{N_C} (1 - \psi_{C_i}) \ \int_0^{I_{max}} f_{I_t^{D/C}}(x)dx \ , \tag{4.15}$$

Thus, the spectral efficiency of UD2D communication in $REG_{D/C}$ regions $\eta_D^{D/C}$ is:

$$\eta_D^{D/C} = Prob(D|D/C)\ E\Big\{\log_2\Big(1+\frac{P_D d_D^{-\gamma}}{I_t^{D/C}+\sigma_n^2}\Big)\Big\}, \tag{4.16}$$

Eq. 4.16 can be simplified to:

$$\eta_D^{D/C} = Prob(D|D/C)\int_{-\infty}^{\infty}\log_2\left(1+\frac{(k-1)\sigma_n^2 d_{DC}^{\gamma}}{x+\sigma_n^2}\right)f_{I|ON}^{D/C}(x)\ dx, \tag{4.17}$$

where $f_{I|ON}^{D/C}(x)$ is a conditional PDF of $I_t^{D/C}$ which is:

$$f_{I|ON}^{D/C}(x) = \frac{f_{I_t^{D/C}}(x)}{\int_0^{I_{max}} f_{I_t^{D/C}}(x)dx}\text{for } 0 \leq x < I_{max}$$

Thus, the mean spectral efficiency η_D^{Iw} in the cell is:

$$\eta_D^{UI} = \begin{cases} \eta_D^{D/C}, & \text{if } \mathrm{UE_D} \text{ is in } REG_{D/C} \\ \eta_D^{D\&C}, & \text{if } \mathrm{UE_D} \text{ is in } REG_{D\&C} \\ 0, & \text{if } \mathrm{UE_D} \text{ is in } REG_C \end{cases} \tag{4.18}$$

The η_C^{UI} becomes:

$$\eta_C^{UI} = \begin{cases} \psi_C \log_2(1+k\Gamma_C), & \text{if } \mathrm{UE_D} \text{ is in } REG_{D/C} \text{ or } REG_C \\ \psi_C \log_2(1+\Gamma_C), & \text{if } \mathrm{UE_D} \text{ is in } REG_{D\&C} \end{cases} \tag{4.19}$$

By defining the geographical positions and the QoS requirements in the cell, the CoI is divided into many regions in which they are classified as:

1. Region $REG_{D\&C}$ in which both cellular and UD2D communication are simultaneously performed using the full RB in frequency and time dimensions). The η_{total}^{UI} is:

$$\eta_{total}^{UI} = \eta_D^{D\&C} + \psi_C \log_2(1+\Gamma_C) \tag{4.20}$$

   The UD2D communication is performed in this region if:

   - $Prob(D|D\&C) \neq 0$.

- $$\frac{\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\ \Gamma_C \sum_{i=1}^{N_C} \left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma} + 1} \geq \frac{\Gamma_D}{k-1} \tag{4.21}$$

2. Region $REG_{D/C}$ which is close to $\mathrm{UE_C}$ and far from BS. In this region, the $\mathrm{UE_D}$s can share the full RB (full in frequency dimension but partially in time dimension) with the cellular network when the $\mathrm{UE_C}$ is in OFF period. The η_{total}^{UI} is:

$$\eta_{total}^{UI} = \eta_D^{D/C} + \psi_C log_2(1 + k\Gamma_C) \tag{4.22}$$

The UD2D communication is performed in this region if:

- $Prob(D|D/C) \neq 0$ and $Prob(D|D\&C) = 0$.
- $$\frac{\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\ \Gamma_C\ \sum_{i=1}^{N_C} \psi_{C_i}\left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma} + 1} \geq \frac{\Gamma_D}{k-1} \tag{4.23}$$

3. Region REG_C which is close to BS. In this region, the $\mathrm{UE_D}$s can not share any RB with the cellular network. The η_{total}^{UI} is:

$$\eta_{total}^{UI} = \psi_C \log_2(1 + k\Gamma_C) \tag{4.24}$$

The UD2D communication is not performed in this region if:

- $Prob(D|D\&C) = 0$ and $Prob(D|D/C) = 0$.
- $$\frac{\left(\frac{d_{DC}}{d_D}\right)^{\gamma}}{k\ \Gamma_C\ \sum_{i=1}^{N_C} \psi_{C_i}\left(\frac{d_{C_i}}{d_{C_iD}}\right)^{\gamma} + 1} < \frac{\Gamma_D}{k-1} \tag{4.25}$$

In this region there is no possibility to perform UD2D communication due to low P_D according to Eq. 3.4, which is less than P_{Dmin} (as in Eq. 3.6).

Figure 4.3 shows a flowchart which explain the operational procedure of UI access paradigm according to the region in CoI. The UD2D communication using UI access paradigm performs efficiently when the $\mathrm{UE_D}$s are in $REG_{D/C}$ because it avoids the interference from the closest $\mathrm{UE_C}$s by exploring the free spectrum holes in the band. However, at $REG_{D\&C}$ the Un performs efficiently the UD2D communication when $\mathrm{UE_C}$s are either ON or OFF (explores the spectrum holes of the far $\mathrm{UE_C}$s).

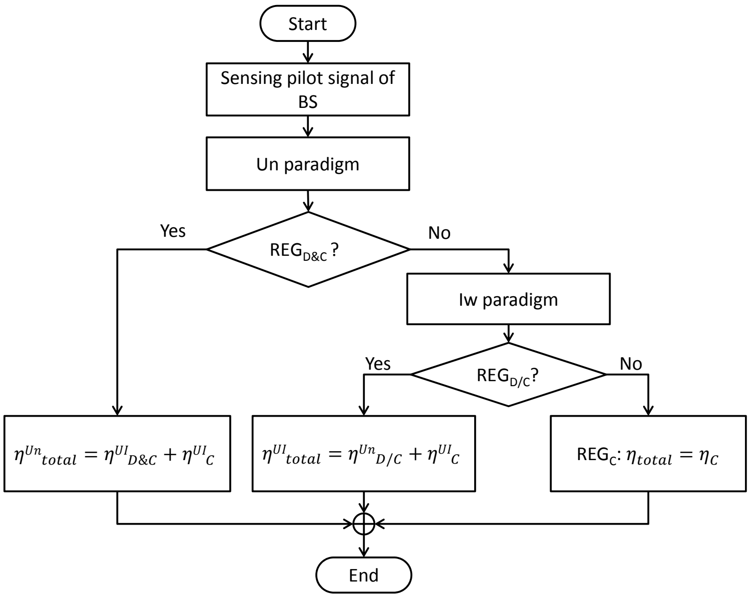

Figure 4.3: Flowchart of UI access paradigm

4.4 Numerical Simulation

To evaluate the performance of UD2D communication in the aforementioned modes (underlay and underlay-interweave), a numerical simulation using MATLAB simulator is performed in this chapter. The general simulation scenario includes 7 neighbor cells with equal cell radius R_C and frequency reuse of 1 (inter-cell interference scenario), as shown in Fig. 3.2 (a). Each cell has a BS (with interference margin k and SINR threshold Γ_C) and a $\mathrm{UE_C}$ with distance to BS d_C. The CoI is the middle cell which has $\mathrm{UE_D}$s with a distance to BS d_{BSD}. All the $\mathrm{UE_C}$s have same packet arrival rate ψ. The UD2D communication is performed in the UL band with a threshold SINR Γ_U. The step size between the positions of $\mathrm{UE_D}$s S is 20 m. The $\mathrm{UE_D}$-Rx has only horizontal displacement from the $\mathrm{UE_D}$-Tx. Table 4.1 shows the assumptions of the system model.

4.5 Evaluation

Spectral efficiency is the metric which measures the maximum number of bits to be transmitted in duration of one second using one Hertz channel bandwidth without errors in the transmission. However, many different factors have impacts on the spectral efficiency of the UD2D communication and the total system in the cell using different access paradigm schemes. These factors are: i) the distance between the $\mathrm{UE_D}$s d_D at

Table 4.1: Assumptions

Parameter	**Value**
Cell radius R_C (Km)	10
Cellular SINR threshold Γ_C (dB)	10
$\mathrm{UE_C}$ ON probability ψ_C	0.5
UD2D SINR threshold Γ_D (dB)	5
Pathloss component γ	3
Interference margin k (dB)	3
Noise floor σ_n^2 (dBm)	-110

different positions; ii) the Γ_C and k at different positions; and iii) the geographical positions of cellular entities and the $\mathrm{UE_D}$s.

In the next subsections, the impacts of these factors are shown using the proposed access paradigm (UI) and the Un.

4.5.1 Impact of Distance between $\mathrm{UE_D}$s

The distance between the communication peer is inversely proportional to the received signal strength at the receiver as in Subsection 3.5.1.

Figures 4.4 (a), (b), (c) and (d) show the η_D at each position in the cell with different d_D/R_C values (1% and 3%) using Un and UI access paradigms. The Un and UI access paradigms have outage in performance η_D when the d_D/R_C is increased. The increment in d_D/R_C degrades the received signal strength at the $\mathrm{UE_D}$-Rx, which may not meet the constraint ($\Gamma < \Gamma_D$). The reason behind this drop is due to the limitation of P_D which can not be increased with the increment in d_D/R_C. Figures 4.4 (c) and (d) show that the UI paradigm outperforms the Un paradigm in η_D due to the UD2D communication in REG_C regions in UI, which are not possible using Un paradigm. The $\mathrm{UE_D}$ at UI paradigm invests the OFF periods of $\mathrm{UE_C}$ in REG_C region to perform D2D communication at REG_C. Thus, the improvement of η_D using UI access paradigm depends mainly on the ψ_C of the $\mathrm{UE_C}$ in the CoI.

Figures 4.5 (a) and (b) show the CDF of the η_D and η_{total}, respectively, using Un and UI access paradigms over different d_D/R_C. The UI paradigm outperforms the underlay mode due to: 1) the reuse of RB at the positions which are close to the interference but during their OFF periods; 2) the reuse of RB at far positions from interferes during their OFF periods (no interference from them), as well as during ON period (when the interference is less than the threshold value). Thus, the achievable improvement in η_D at different positions in the cell depends mainly on ψ, which improves the η_{total}.

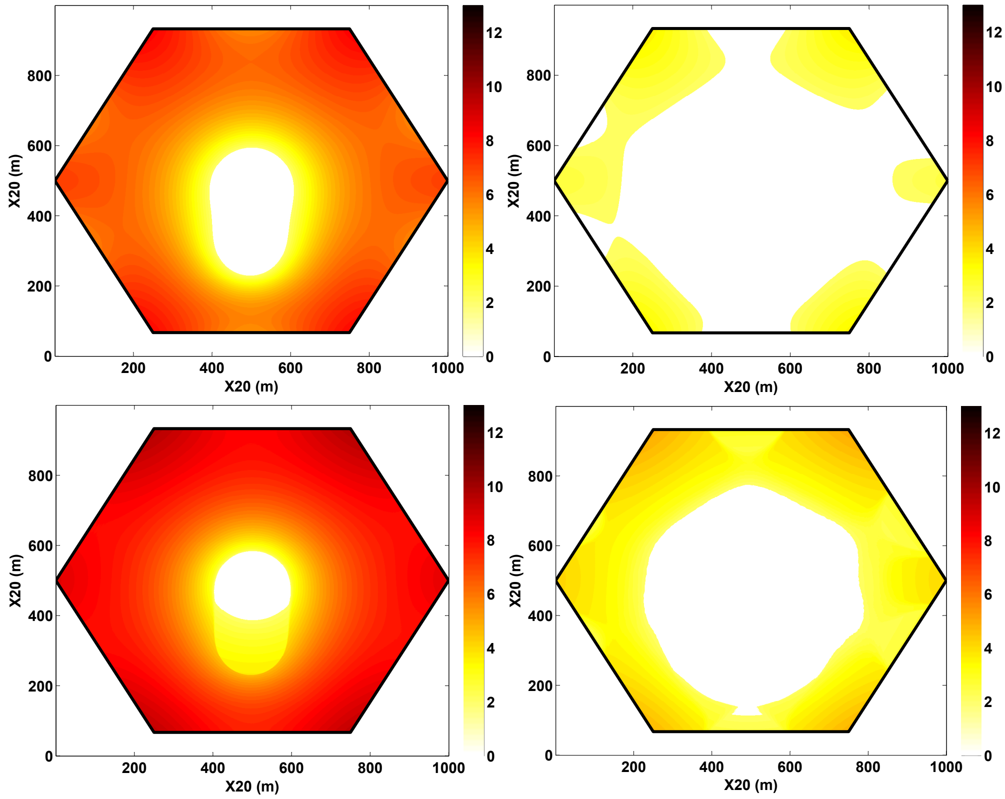

Figure 4.4: η_D over the cell with d_D/R_C of: (a) 1% using Un paradigm, (b) 3% using Un paradigm, (c) 1% using UI paradigm, and (d) 3% using UI paradigm

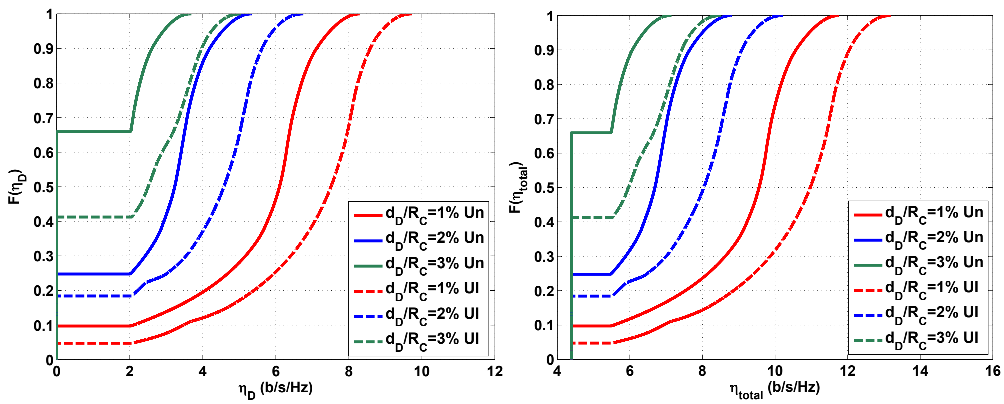

Figure 4.5: Comparison of cdf of: (a) η_D, (b) η_{total}; using Un and UI access paradigms over different d_D/R_Cs

Figure 4.6 shows the percentage of effective UD2D communication area in the cell using Un and UI access paradigms with different d_D/R_C. The UI outperforms the Un

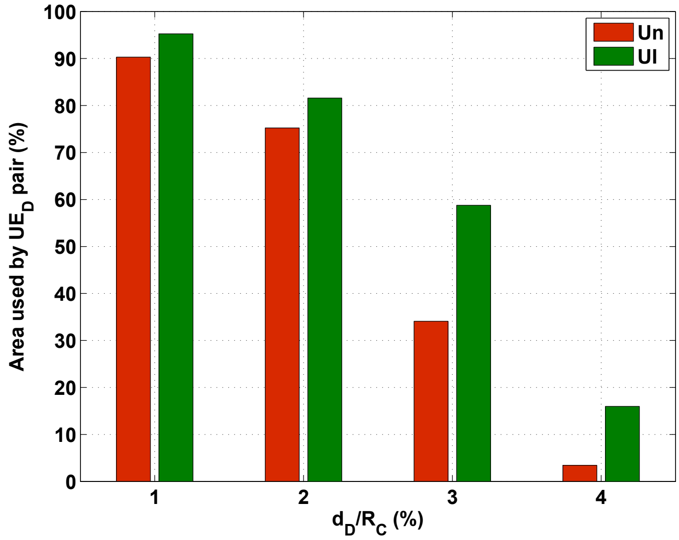

Figure 4.6: Comparison between the area used for UD2D communication in the cell using Un mode and UI mode over different d_D/R_C

paradigm in the effective UD2D communication area in the cell even with the increment of d_D/R_C. The improvement in the effective UD2D communication area is due to the possibility of utilizing the resource block in during the OFF period which does not include interference from UE$_\mathrm{C}$s. This leads to a higher Γ when using the same d_D in the Un paradigm.

4.5.2 Impact of Cellular SINR and Interference Margin

Applying Un access paradigm makes the UD2D communication restricted to the performance of cellular system which is represented by Γ_C. This value has an impact on the η_D, η_C and η_{total}. However, the value of the impact depends on the geographical positions of cellular entities and the UE$_\mathrm{D}$s in the cell. Evaluating the performance of UI and Un access paradigms necessitates a study the impacts of geographical positions and QoS requirements (such as Γ_C) on the performance of UD2D communication (η_D), cellular communication (η_C) and system capacity η_{total}.

To perform such study, two different positions of UE$_\mathrm{D}$ pair (which have different inter-cell interference, intra-cell interference and limitations in transmit power) have been studied that UE$_\mathrm{D}$ pair is located at cell edge and cell center, as shown in Fig. 3.9 (a) and (b), respectively. In both positions, the UE$_\mathrm{D}$ pairs use d_D/R_C of 1%.

At cell edge, UI paradigm has improved the η_D and η_{total}, compared to Un paradigm with different values of Γ_C, as shown in Fig. 4.7 (a). This improvement is due to: i)

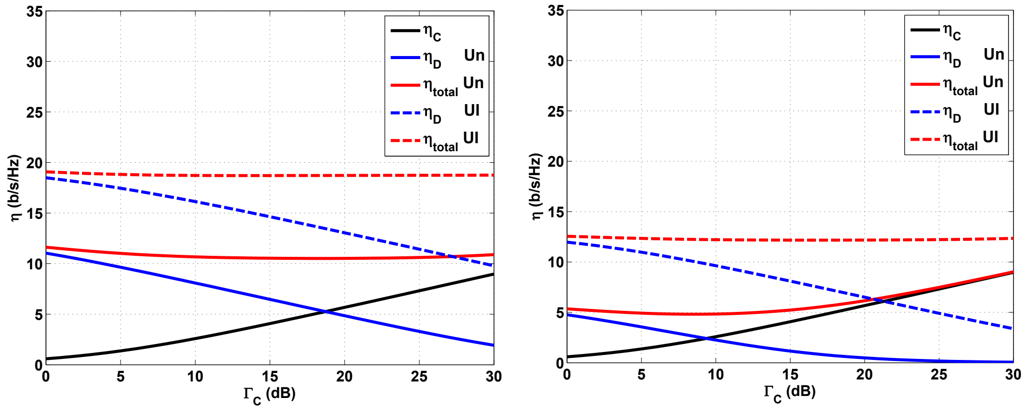

Figure 4.7: The influence of Γ_C on η_D, η_C, and η_{total} at: (a) cell edge, (b) cell center

the utilization of OFF periods of the close $\mathrm{UE_C}$s which leads to lower interference at the $\mathrm{UE_D}$-Rx and reduces the influence on the Γ; and ii) the large distance from BS and $\mathrm{UE_C}$ which allows the $\mathrm{UE_D}$-Tx to increase the P_D and to receive low intra-cell interference. Thus, the $\mathrm{UE_D}$ can perform UD2D communication over free and occupied RBs at the cell edge, assuming low inter-cell interference from nearby neighbor cells.

At the cell center, the UI paradigm still outperforms the Un paradigm in η_D and η_{total}, as shown in Fig. 4.7 (b). However, this improve is low, compared to cell center, due to short d_{BSD} which limits the P_D and short d_C which yields a high intra-cell interference. Thus, the $\mathrm{UE_D}$ pair performs UD2D communication only within OFF periods of $\mathrm{UE_C}$ in which the RB is free and no intra-cell interference.

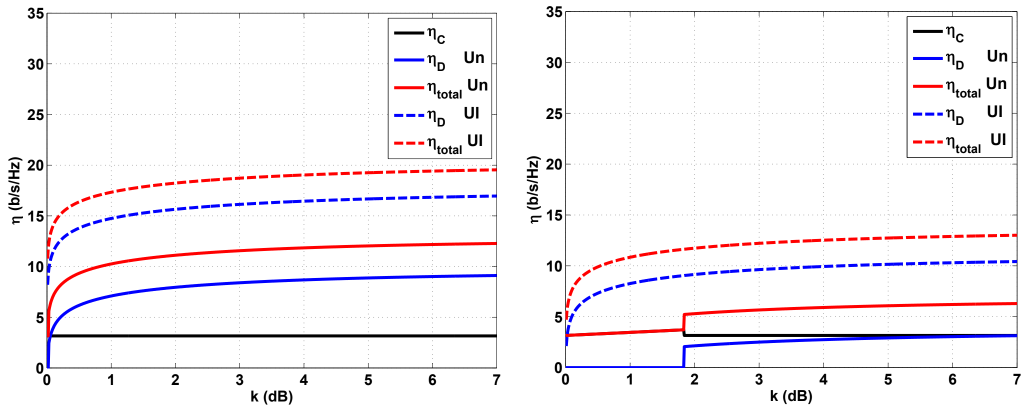

Figure 4.8: The impact of k on η_D, η_C, and η_{total} at: (a) cell edge, (b) cell center

Figures 4.8 (a) and (b) show the impact of k on the η_D, η_C and η_{total} at cell edge and cell center using Un and UI access paradigms, respectively. At the cell edge, low value of

k allows the UE$_D$s to perform UD2D communication due to the far distance from the BS which allows the UE$_D$ to increase P_D according to Eq. 3.4 which increase the achievable Γ. However, applying UI improves η_D and η_{total} while keeping η_C unchangeable due to using the RBs at ON and OFF periods, which leads to increase the achievable Γ, as shown in Fig. 4.8 (a).

At cell center, the k has low impact on the η_D using Un paradigm due to the short distance between the UE$_D$ and the BS, which decreases the upper limit of P_D. Thus, the achievable Γ is low and yields a low η_D and η_{total}. However, by using UI the impact of k on the η_D and η_{total} is higher due to the usage of RBs in OFF periods, as shown in Fig. 4.8 (b). At this position, the Un paradigm may wont be useful if the Γ_D is high and the alternative solution is to use UI access paradigm.

4.5.3 Impact of Geographical Positions of UE$_C$ and UE$_D$ pair

The geographical positions of cellular entities and the UE$_D$ have an impact on the UD2D communication performance [KA08, KLA13]. The geographical positions of the entities (BS, UE$_C$s and UE$_D$s) make different path losses between the entities them selves, which have positive and negative impacts on the η_D and η_{total} according to the position of the entities, as shown in Fig. 3.23.

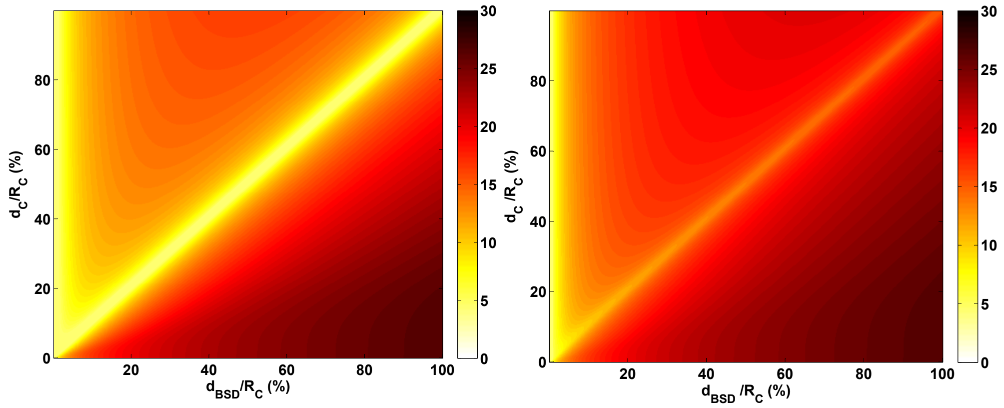

Figure 4.9: The relation between η_{total}, d_C and d_{BSD} in the cell using: (a) Un paradigm, (b) UI paradigm

Figures 4.9 (a) and (b) show the impacts of geographical position of UE$_C$ (d_C) and UE$_C$ (the distance between UE$_D$ and BS d_{BSD}) in the cell on η_D using Un and UI paradigms, respectively. The UI paradigm outperform Un paradigm at positions close to UE$_C$ and in between BS and UE$_C$. The improvement in UI is due to exploiting the RBs at these position during the OFF periods of UE$_C$ which leads to very low intra-cell interference at UE_D-Rx, compared to Un paradigm. Thus, UD2D communication is performed in more area in the cell with higher η_D, compared to Un paradigm, especially some position which are close to BS, as shown in Fig. 4.9 (b).

4.6 Summary

The CR-equipped UE_D pair perform UD2D communications in CoI using two different access paradigms: Un and Iw access paradigms. By using Un paradigm, any UE_D pair uses the RBs without generating a harmful interference with the cellular entities (BS in UL and UE_C in DL). The drawbacks of Un paradigm are: i) interference from cellular entities; ii) limitation in P_D; and iii) limited positions in the cell in which the UD2D communication is performed.

By using Iw paradigm, the UE_D uses RBs opportunistically to perform the UD2D communication. Thus, the UE_D uses the common free RBs (on both sides) to perform the UD2D communication efficiently with no limitation of P_D. However, the drawbacks of Iw paradigm are: i) ensuring free RB on both sides of communication simultaneously; and ii) possibility to generate interference at the C-Rx (BS) if the UE_C changes his activity ψ_C.

To conquer the aforementioned drawbacks, a new access paradigm is proposed in this chapter which merges the Un and Iw access paradigms. The proposed paradigm is called UI, which exploits the RBs of the cellular entities during their OFF periods at positions close to them efficiently using only free RBs at UE_D-Rx. Also, it ensures no interference with the BS if the UE_C changes its activity ψ_C. Thus, the UI increase spectral diversity of the system, system capacity and reduce the resource consumption in the cell.

Applying UD2D communication in cellular band using UI paradigm improves the system capacity and spectrum utilization by reusing the free portions of RBs for unlicensed users. However, performing UD2D communication using UI paradigm is influenced by different factors (such as noise power, interference, UE_Cs activities, shadowing, etc.) which have dynamic behavior over time and may leads to have a link failure between the communicating UE_D pair. To conquer such issue, there is a need to perform link adaptation process by the communicating UE_D pair to adapt their link according to the aforementioned factors. To keep the performance of UD2D communication efficient under dynamic radio environment, there is a need for an algorithm which adapts the link under such dynamic radio environment and improve the performance from different aspects.

5 Self-Organizing Link Adaptation (SOLinA) Algorithm

Contents

Applying CR technique in UD2D communication shows an improvement in total system capacity due to the orthogonal usage of spectrum holes (in time dimension) relative to cellular user signal. However, the dynamic behavior of the radio environment and the geographical positions of cellular entities have influences on the performance of the UD2D communication (positive and negative). Such a case makes the link quality of UD2D communication suffers from many degradations during the communication process which leads to drop the link between the UE_Ds. Thus, there is a need for a Cognitive Engine (CE) that reacts autonomously to the environmental changes and other effects by adapting the radio parameters to optimize the system performance [RLRB04, Rie04, NBW$^+$07, dBMP08]. Several algorithms have been proposed as a CE to optimize CR performance within UD2D communication under environmental changes. However, some aspects have not been studied such as cellular user activity, the positions of the cellular entities in the cell and how the best sub-channel is selected (sub-channel is equivalent to sub-carrier).

In this chapter, a self-organizing algorithm for CR-based UD2D communication is introduced which autonomously adapts the radio parameters to meet the desired QoS requirements under dynamic radio environment. The proposed algorithm is called Self-Organized Link Adaptation (SOLinA) algorithm and consists of three entities: Cross-Layer Optimization (CLO), expert system and learning entities. The CLO entity is based on Adaptive Discrete Particle Swarm Optimization (ADPSO) algorithm which is a heuristic algorithm to determine the configuration of radio parameters. The expert system entity is based on Case-based Reasoning (CBR) algorithm which applies the previous radio parameters within similar environmental state. The learning entity is based on Reinforcement learning method which learns the behavior of the radio environment so as to speed-up the convergence of the system.

This chapter is organized as follows: The system model is presented. The interaction between $\mathrm{UE_D}$ and the radio environment is defined. Then, the problem formulation is discussed. The literature related to link configuration using CR technology have been studied. Later, the proposed link adaptation algorithm is presented in which the different entities inside the algorithm are explained in details.

5.1 System Model of UD2D Link Adaptation

The system model consists of cellular network and $\mathrm{UE_D}$ pair, as shown in Fig. 5.1. The cellular network is represented by one macro cell of a radius R_C surrounded by neighbor cells with a frequency reuse of 1. Each cell consists of a BS and number of $\mathrm{UE_C}$s distributed in the cell. The BS is equipped with omnidirectional antenna and its spectrum band is divided into UL and DL sub-bands using FDD scheme. The UL sub-band is divided into number of sub-channels with frequency f_C. Each sub-channel consists of number of sub-carriers using Orthogonal Frequency Division Multiplexing (OFDM) technique. The system also uses TDMA to generate resource blocks (RBs) which represent the time slot in which the $\mathrm{UE_C}$ uses the sub-channel f_C. The BS broadcasts a pilot signal S_{BS} with a per-defined transmit power P_{BS} and interference

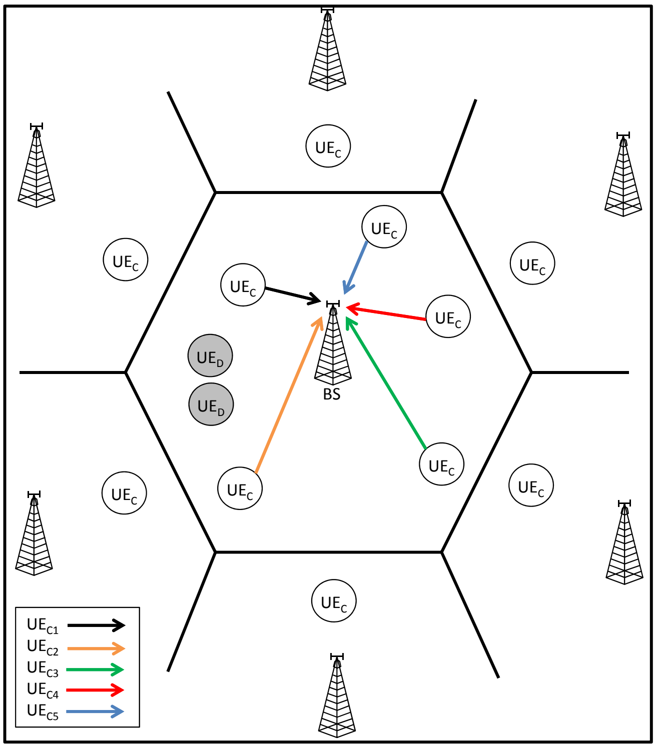

Figure 5.1: System model of UD2D link adaptation

margin k. Each UE$_\mathrm{C}$ adapts its transmit power P_C according to the threshold SINR of BS Γ_C, interference margin k and the path loss to BS d_C^γ in UL sub-band, as in Eq. 3.2.

Each UE$_\mathrm{D}$ is equipped with CR technology (unlicensed user) to perform cognitive communication in UL sub-band. The UE$_\mathrm{D}$ uses wide band spectrum sensing to detect the activities of UE$_\mathrm{C}$s efficiently over different sub-channels in UL sub-band. The UE$_\mathrm{D}$-Tx senses the S_{BS} to estimate the path loss to the BS d_{BSD}^γ (assuming a predefined P_{BS}). Also, UE$_\mathrm{D}$-Tx determines Γ_C and k from the S_{BS}. The UE$_\mathrm{D}$s attempts to establish a UD2D communication link using UI access paradigm at different positions in CoI. Thus, the UE$_\mathrm{D}$-Tx uses Eq. 3.4 to determine its upper bound of transmit power P_{Dmax} using Un access paradigm. While the UE$_\mathrm{D}$-Rx is the victim of any interference from the UE$_\mathrm{C}$ I_C, it decides the f_C which has less I_C so as to meet the desired QoS requirement ($\Gamma \geq \Gamma_D$). Thus, the UE$_\mathrm{D}$-Tx and UE$_\mathrm{D}$-Rx decide both how much P_D to transmit over which f_C in the UL sub-band of the cellular spectrum.

5.2 Interaction with Radio Environment

Studying the link adaptation of UD2D communication under dynamic radio environment necessitates defining the interaction between UD2D radio parameters, QoS requirements and the surrounding radio environment. This interaction is represented by retrieving observations from the radio environment, and applying the configuration of radio parameters to meet the desired QoS requirements [PKM+12]. The interaction depends on the inputs to the UE_D pair and the outputs from it. Figure 5.2 shows the interaction between UD2D communication pair and the surrounding radio environment.

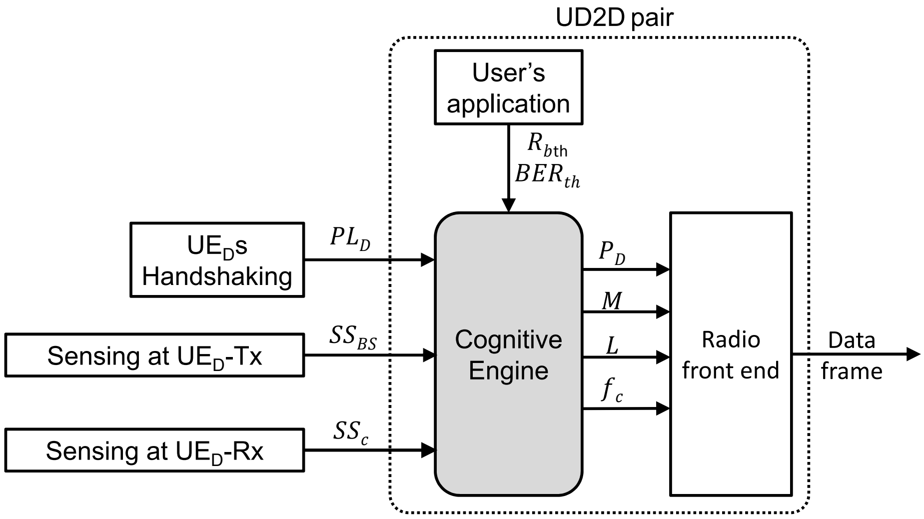

Figure 5.2: The interaction between the UD2D communication pair and the radio environment

The UD2D pair consists of radio front end and the CE which is responsible for configuring the radio link. The input to the UD2D pair (which goes inside CE) includes:

1. Environmental observations:
   - The BS pilot signal S_{BS}, which is sensed at the UE_D-Tx. This signal includes information about k and Γ_C. Also, the UE_D-Tx uses this signal to derive the path loss to the BS d_{BSD}^{γ}.
   - The signal strength SS_C over each f_c which is sensed by UE_D-Rx's.
2. The signal strength of the peer UE_D SS_D over the control channel (handshaking with a predefined power), which is used to derive the path loss between the UE_D pair d_D^{γ}.

3. The minimum QoS requirements for user application:
   - Minimum bit rate $R_{b_{th}}$
   - Minimum Bit Error Rate BER_{th}

while the output from the CE includes the configuration set of the radio parameters which represents the action on the UD2D communication. This output includes:

1. Transmit power P_D
2. Modulation scheme M
3. Frame length L
4. Sub-channel frequency f_C

5.3 Problem Formulation

Due to the dynamic behavior of the radio environment, the quality of UD2D communication link may suffer from degradations. Overcoming the negative influences of such dynamic environment necessitates applying a CE which reacts autonomously to the environmental changes to improve the performance of the system. The CE has to conquer some challenges related to radio environment, as well as the application in the $\mathrm{UE_D}$s. These challenges can be classified into three different classes: i) interdependency between link objectives, ii) computational overhead, and iii) stochastic radio environment.

In the next subsections, these challenges are explained in details.

5.3.1 Inter-dependency between Link Objectives

In a real-world problem, different link objectives (such as maximizing throughput, minimizing energy consumption, minimum spectrum handover, minimum delay, minimum interference, etc.) pushes the adaptive communication system to configure its radio parameters in order to meet the desired QoS requirements under the desired link objectives. However, due to numerous interdependencies between the link objectives, the search space of radio parameters have sets of non-dominated configurations which optimize the system in one objective at the expense of other objectives. This problem is called the Multi-Objective Optimization Problem (MOOP) which is arose when the optimization algorithm explores the search space to find an optimal trade-off solution for the conflicted link objectives (such as maximum throughput and minimum energy consumption) [Deb05],[MA04],[NBW$^+$07],[KCS06]. Thus, the interdependence between different link objectives and with various radio parameters makes the optimization process more sophisticated, as shown in Fig. 5.3 [Fet09].

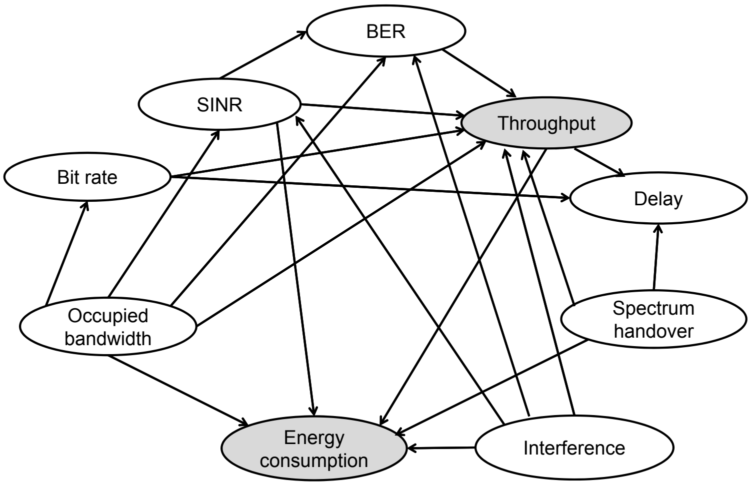

Figure 5.3: The interdependence between different link objectives [Fet09].

5.3.2 Computational Overhead

One of the main goals of any communication system is to decide autonomously and act instantaneously to achieve fast convergence in link adaptation processes, in accordance to the observations and application requirements. Meanwhile, owing to the dynamic radio environment, the UD2D communication system suffers from high computational efforts and signaling overhead to reconfigure its link at any change in the radio environment. Also, rapid changes in the radio environment may cause the configuration of radio parameters to lack the desired link objectives and QoS requirements. Thus, there is a need to propose a set of predetermined actions that achieve the requirements under different observations.

5.3.3 Stochastic Radio Environment

Applying any communication system in a dynamic radio environment with stochastic behavior has some influences on the performance of the system. One of the main influences is UE_C activities over the channel which may lead to spectrum handover by UD2D communication. Such a case leads to an increase in the spectrum handover which has negative impacts on the performance of the system. While the UE_C activities over the channels vary in time, there is a need to learn radio environment behaviors (including the UE_C activity, fading, shadowing, etc.) so as to determine the best configuration of radio parameters that optimizes system performance.

5.4 Literature Survey

Different algorithms have been implemented as CE to conquer the aforementioned challenges, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Fuzzy Logic Control (FLC), Ant Colony Optimization (ACO), Artificial Neural Network (ANN), Q-Learning, Case-Based Reasoning (CBR), Rule-Based System (RBS). The aforementioned techniques are classified into: i) optimization techniques; ii) expert system techniques; and iii) learning techniques.

In the next sub-sections, the literature survey about the previous work is presented, in addition to their strengths and weaknesses.

5.4.1 Optimization Technique

Many optimization techniques have been used to optimize the performance of CR node by determining the best radio parameters which meet QoS [Fet09]. The optimization technique uses link objectives to validate the proposed radio parameters under current observations.

A detailed description of the most popular heuristic algorithms-based optimization techniques, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), are explained in this sub-section. Also, their applications, strengths, and weaknesses are discussed.

Genetic Algorithm

The Genetic Algorithm (GA) is a biologically inspired searching algorithm used to solve optimization problems. It has been used to solve problems related to data fitting, difficult scheduling, and trend spots. The GA works on a set of solutions (a population) in parallel, which can explore the search space.

Some previous work has proposed GA to solve multi-objective optimization problems (such as low bit error rate and low power consumption) under different QoS requirements for user's applications [RLRB04, Rie04]. In [NBW$^+$07], the authors proposed that the GA can optimize CR performance in multi-carrier systems where each sub-carrier has its own radio parameters to re-configure, as in IEEE 802.11.

The idea of implementing the GA as a CLO approach has appeared in [New08, dBMP08]. The authors proposed GA to adapt the radio parameters from physical (PHY), Medium Access Control (MAC) and Network (NET) layers under different link objective with multi-carrier systems.

In [dBMP08], the authors applied the ARQ technique within the GA, in order to validate the radio parameters at the CR receiver side. However, the drawback is the application of the ARQ-technique for every chromosome in the population per each iteration, which causes high signaling overhead.

In [CW09], the authors proposed a GA-based algorithm to improve the spectrum allocation for distributed CR nodes in order to achieve efficient-spectrum utilization. The authors focused on distributing the sub-carriers over different spectrum holes to avoid interference with PUs. However, the authors did not focus on optimizing the number of required sub-carriers for their applications scenarios.

In [CNEW10], the authors developed the GA used in [NBW$^+$07] by implementing accelerating scheme based on the seeds of previous actions, in addition to adapting the ranges of each dimension in the search space according to the user's application.

In [SLB13], the authors proposed a real coded GA to solve in multi-carrier systems within multi-objective optimization problem. The proposed algorithm in [SLB13] showed an improvement in the convergence time.

The GA has, according to [MMKMT12], several drawbacks including:

- Lots of time is required to find optimum parameters that achieve the convergence criteria, which may become useless if the CR works in a dynamic radio environment.
- The fitness value is negatively affected by the increasing number of objectives, especially with MOOP.
- Increasing the number of radio parameters also has a negative influence on the fitness value, especially with multi-carrier systems where there are two or more parameters for each sub-carrier to optimize.

Ant Colony Optimization

Ant Colony Optimization (ACO) was inspired from the experiments of Goss on real colony of ants to chose the shortest path between different paths [GADP89]. To optimize a system with non-deterministic polynomial problem (NP-hard), ACO uses a variable called artificial pheromone trail on each path (possible solution), which is proportional to the utility of the path. The decision of each ant depends on computing probability of the shortest path (according to its utility) [DB10].

The authors in [WC09] proposed binary version of ACO (BACO) algorithm for multi-carrier systems with a set of link objectives. The proposed algorithm showed an improvement in convergence time and fitness value compared to GA. However, their work did not study the influence of CLO on the convergence time of the system.

In [ZLW12], the authors proposed a mutated ACO (MACO) based CE for multi-carrier system to solve MOOP. The proposed algorithm showed improvements in convergence time and fitness value, compared to GA. However, their work did not study the influence of CLO and higher number of sub-carriers on the convergence time and the fitness value of the system.

In [HFWZ12], the authors proposed an improved version of ACO algorithm for radio parameters reconfiguration under dynamic radio environments. The proposed algorithm integrates different mechanisms to improve the performance of ACO. The evaluation showed flexibility in reconfiguration operation. However, the authors did not compare the performance of their proposed algorithm with the literature.

According to [MDBH$^+$07, HBN$^+$10], some limitations are in ACO including:

- Computational time is still high compared to other algorithms.
- Inferior to other algorithms for local searches.

Particle Swarm Optimization

Particle Swarm Optimization (PSO) was invented during a simulation of graceful motion of swarms of birds as part of a study investigating the idea of "collective intelligence" in biological populations [KE95]. The PSO is an evolution algorithm that applies swarm theory to solve optimization problems. The early implementation of PSO in different fields shows its effectiveness in solving MOOPs, comparing to other optimization algorithms [ES98, HCDWV05].

The authors in [ZXZS09] proposed a Discrete version of the PSO (DPSO) algorithm for adapting radio parameters of multi-carrier system with MOOPs. The proposed algorithm showed improvements in convergence time and fitness value, compared to the GA. However, their work did not study the influence of CLO on the convergence time of the system.

In [XZL09], the authors proposed a PSO-based algorithm for adaptive power and bit allocation of DL Orthogonal Frequency Division Multiplexing (OFDM) in multi-user CR systems under interference tolerance and a power ceiling.

Another application of PSO was performed in [ZZLC09], where the authors proposed a PSO-based channel allocation algorithm between different SUs. This work showed an improvement in fitness value of the reward and fairness objectives, compared to GA.

According to [SE99], PSO-algorithm has some drawbacks that affect its performance as an optimization technique, including:

- A probable failure in determining the required optima in case of MOOP and wide search space.
- A slow fine tuning ability of the search area around the optima.

5.4.2 Expert Systems Technique

An expert system technique is a system that uses past experiences to solve similar problems by using AI-based algorithms [New08]. Implementing expert system techniques in CR nodes leads to a reduction in computational efforts, convergence time, and signaling overhead for link establishment and sub-channel handover processes. Several different algorithms of expert system have been applied in CR field such as CBR, RBS and FLC.

Case-Based Reasoning

Case-Based Reasoning (CBR) is of one the expert system algorithms that depend on the past experiences to perform an action for current observation. CBR is a problem solving paradigm which is able to utilize the previous knowledge of the environment as facts from experience [AP94]. CBR is also studied within cognitive science as a model of human reasoning. One motivation for using CBR is to increase efficiency by reusing prior reasoning rather than generating solutions from scratch [Lea].

In [HGB+09], the authors developed a CBR algorithm for IEEE 802.22 Wireless Regional Area Network (WRAN) applications. The performance of CBR shows a fast link adaptation, compared to the GA and Hill Climbing Search (HCS).

Another application of CBR was explored in [HLH10], in which the authors proposed a CBR algorithm to solve the problems of limited storage space and MOOP. The proposed algorithm is based on Divide-and-Conquer techniques to apply CBR in the CR.

According to [HBN+10], the main limitations of CBR include:

- Irrelevant state-action pairs can be included. Thus, the search space is unnecessary increased.
- In some applications, there are limitations in system rely on previous actions.

- Unstable environments require more memory, which has an impact on the speed of reasoning process.

- Conservative solutions degrade the performance of the system.

Rule-Based System

Rule-Based Systems (RBS) are another algorithm in applying expert system technique, where rules are extracted from previous applications and used in the decision making process [HBN+10]. The typical RBS algorithm consists of rules that define the conditions and their related actions, and the inference engine which defines specific actions according to the input and the rule data-base [IP13].

In [CHSO07], the authors defined a generic architecture of CR node that combines a learning engine with RBS. The learning results can be expressed in the rule data base and can therefore be used for future states.

In [WSG07], the authors proposed an AI-based algorithm to derive the rules for RBS during the experiments over a vast parameter space. The best radio parameters for specific sub-channels conditions and application requirements can be derived based on the extracted rules.

The main limitations of implementing RBS in CR are [HBN+10]:

- Perfect domain knowledge is not always available for applications, which has an important impact on the quality of the decision.

- Tedious process of rule deviation for a complex domain.

- Might have an inappropriate response if the domain is not perfectly understood.

Fuzzy Logic Control

Fuzzy Logic Control (FLC) is an inference method that is most similar to the way humans think and to natural language, reflecting the inexact nature of the real world. The FLC can achieve a fast automatic control system based on linguistic control and user knowledge of the surrounding environment [Lee90]. The FLC has been applied in CR nodes to perform different tasks related to decision making.

The authors in [GPN08] proposed an FLC-based algorithm for CE to perform an effective spectrum hand-over decision under dynamic radio environment with uncertain, incomplete, and heterogeneous information. However, their sub-channel model was not clear and the influences of mutual interference between PU to CR node were not considered in the model.

In [BZ08, BZ09], the authors proposed an FLC-based algorithm as a CLO for CR to solve single and MOOPs. The proposed approach in [BZ09] estimates the expected transport-layer performance, and then uses the proposed algorithm to choose a suitable access opportunity by comparing achievable QoS requirements. Nevertheless, the proposed system did not analyze the performance of CR under dynamic radio environment.

In [KS09], the authors proposed FLC-based CR as a core of reasoning for CR Worldwide interoperability for Microwave Access (WiMAX) systems. The proposed algorithm showed improvements in a number of errors and in convergence time compared to Case-Based Reasoning (CBR).

According to [Sug85], the main drawbacks of using FLC-based algorithm are

- Limitations in the knowledge acquisition process, where it defines the shape of member functions for the input and output parameters.
- A lack of a systems theoretic framework, as well as a lack of analytic tools for its utilization.

5.4.3 Learning Technique

Many learning techniques have been used in the CE to define a model of unknown radio environment for CR. By using learning technique, CR can learn the influence of radio environment and applied actions on the performance of CR communication. Several different learning techniques have been applied in CR such as ANN and Q-Learning.

Artificial Neural Network

The Artificial Neural Network (ANN) is a simple system that is made up of a number of processing elements which process the information by their dynamic state response to external inputs, just like a human brain [Cau88]. Modeled on a nerve plexus, the ANN is a set of nonlinear functions with adjustable parameters that can be used to create a desired output [Hay94]. The ANN has the ability to learn and to be trained autonomously during the operation of the system. It can learn the features of the system, and assists the adaptation of radio parameters in order to achieve the desired communication link in the CR node [HBN^{+}10].

In [ZX07], the authors proposed the usage of the Levenberg-Marquardt (LM) algorithm-based ANN algorithm to learn the best radio parameters needed to meet the QoS requirements.

In [HTM+07], the authors applied ANN-based neurodynamical algorithm to optimize a large scale heterogeneous wireless network environment. The proposed algorithm in [HTM+07] showed an improvement in the average throughput per CR node compared to the game theory.

In [PvO13], the authors proposed an ANN-based algorithm to perform spectrum sensing in a CR by learning the PU signal form. The proposed algorithm in [PvO13] showed an improvement in PUs detection, compared to the other energy detection methods.

Another application of the ANN was performed by [LLZ10] to localize PUs in a hidden node scenario. The authors applied Back Propagation (BP)-based ANN algorithm to estimate the position of passive PU receivers based on the cooperation of multiple CR nodes.

The limitations of ANN are [HBN+10]:

- The size of ANN can negatively affect the training speed.
- Over-training is possible to occur.

Q-Learning

Q-Learning (Q-L) is a model-free machine learning technique, in which an agent (through interaction with its environment) learns the best behavior for certain states of the environment [APB+10]. Recently, some researchers have proposed CE based on Q-L to improve the learning and decision making processes in CR.

In [LDCV12], the authors proposed a self-adaptation algorithm based on Q-L to learn the best modulation and coding schemes according to the measured value of SINR. However, the application was limited and did not study the interference with PUs.

In [GSG10], the authors proposed decentralized Q-L to manage harmful interference to PUs and to improve the spectral efficiency of the network.

Another application of Q-L has been explored in [Hus10], where a Q-L based algorithm has been proposed as an Aloha-like spectrum access scheme for multi-user CR network without negotiation between CR nodes.

According to [Tiz06, CZZ10, JGL08], the limitations of Q-Learning are:

- High computational efforts due to visiting all the states with all possible actions frequently to ensure the convergence, which leads to increase the computational efforts.

- It is a requirement to account for opponent's strategies in multi-agent Q-learning, which inapplicable in non-cooperative scenarios.

5.4.4 Hybrid Technique

In addition to the aforementioned algorithms, some researchers tried to improve CR performance by proposing a CE based on combining more than one AI-based algorithm for the specific purpose of reducing the drawbacks of each algorithm. By applying a hybrid algorithm, the CE can improve convergence time, fitness value, spectral efficiency, and spectrum utilization.

In [NRW+07], the author enhanced the work presented in [Rie04] by proposing a combination of the GA and CBR-based population algorithm to determine the amount of seeds to be utilized from the last cognition cycle. This work resulted in an improved convergence time of the GA in addition to reduced computation efforts.

In [ZGM+07], the authors proposed a generic architecture of CEs based on combining CBR and Knowledge-Based Learning (KBL) for IEEE 802.22 WRAN. The proposed CE architecture achieved fast adaptation and near-optimal utility.

In [NH09], the authors introduced a combination of FLC and Q-L as an algorithm for opportunistic sub-channel selection in IEEE 802.11-based wireless mesh. This combination was used to update the utility perceived by each wireless node under different traffic load conditions.

In [Red10], the authors introduced a combination of CBR and Collaborative Filter Approach (CFA) as an algorithm for spectrum allocation in a collaborative game. This combination was used along with the cooperative game concept to select the preferred sub-channel for a cognitive user at any given time slot.

5.4.5 Applying Heuristic Search in Cognitive Radio

Determining a method to optimize the radio parameters of CR becomes an important step toward getting a self-organized system due to the challenges which are explained in Section 5.3. To define a proper optimization method for UD2D communication, many factors must be investigated, including environmental observations (inputs), fitness functions (criteria), and search spaces (outputs).

The nature of the wireless environment makes the optimization problem as a non-linear problem due to the dynamic path loss multi-path behaviors that affect the observations [New08]. The interdependency between link objectives increases the complexity of the optimization problem, which may be increased by increasing the radio parameters to be optimized. As a result, several regions in the search space improve the performance of CR upon different link objectives and user needs [Fet09].

The interference level varies over different sub-carriers in multi-carrier systems due to dynamic multi-path behavior, which also varies over the sub-channel. Such circumstances require optimization of the radio parameters over all sub-carriers to avoid degradation in the QoS requirements. While each sub-carrier has certain interference level, it requires certain values of P_D and M to achieve the desired Γ. Optimizing the configuration of radio parameters in a multi-carrier system (with 64 sub-carriers each having P_D ranges from 0 to 30 with 0.1 dBm steps) and M (BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM) increases the number of possible configuration sets of radio parameters to 99200. Optimization of the radio parameters in such systems becomes as Traveling Salesman Problem (TSP) in which many solutions lead to the goal with different costs (time, quality, etc.). The aim of TSP is to find the configuration of radio parameters which achieves the best performance [ZLW12].

Presence of different dimensions in the search space with conflicting link objectives may lead to some local optima besides the global optimum in the search space. The different local optima make the problem of optimizing radio parameters a non-convex optimization problem. Thus, any method based on some form of gradient search, such as Non-Linear Programming (NLP) optimization methods, becomes inefficient, and in some situations, incapable of finding a feasible solution [New08, Fet09].

Thus, the multi-dimensional large search spaces and the presence of local optima regions makes optimizing the radio parameters more complex than many search and optimization algorithms can handle. Among all of the non-linear optimization methods, the authors [Rie04, RLRB04, dBMP08, CW09, ZPZS09, WNH09, CNEW10, HFWZ12, BYD+14] proposed heuristic algorithms as most suited for these tasks, due to their higher flexibility and significantly less amount of power required to solve the problems.

5.5 Self-Organizing Link Adaptation (SOLinA) Algorithm

Many algorithms have been implemented within the CR technology to perform the link adaptation for unlicensed users under the dynamic radio environment. The link adaptation process includes decision-making and learning, which are parts of the cognition cycle of CR. Decision-making process determines the best configuration of the radio parameters, which optimizes the UD2D communication for the surrounding radio environment. On the other hand, learning process studies the reaction to the applied actions in order to improve the decision-making process (find the best radio parameters configuration to apply). To achieve proper performance of UD2D communication, there is a need to perform decision-making and learning by UE_D pair because there is no central entity responsible for link adaptation (such as the BS in cellular systems). These processes can result in efficient link adaptation for UD2D communication under dynamic radio environment.

In this chapter, a novel algorithm is proposed to efficiently perform link adaptation under the dynamic radio environment by: i) exchanging environmental observations between UE_D in a given pair, ii) optimizing UD2D link performance, and iii) ensuring QoS requirements are satisfied at the receiving end. The proposed algorithm is called Self-Organized Link Adaptation (SOLinA), which is based on distributed computation carried out by both UE_D-Tx and UE_D-Rx to determine link configuration using the UI access paradigm.

SOLinA algorithm consists of three operation phases which are linked to Knowledge Base (KB), as shown in Fig. 5.4. The KB has a table which includes the environmental state st, the applied actions a (the configuration parameters), and the link quality qu due to applying a. The KB is used to fetch previous applied a under similar radio environment to st and high qu (more details are in Subsection 5.5.2.1). The three phases of SOLinA algorithm are:

1. Phase 1: Sensing radio environment which includes: i) sensing the channels on both UE_D-Tx and UE_D-Rx; ii) observing the environmental state st (interference power I_C, probability of UE_C activity $Prob_i$ over each channel f_C, and pathloss between the UE_Ds); iii) exchanging the observation between communicating UE_Ds; and iv) sending st to KB.

2. Phase 2: Making decision of which configuration should be applied to the link. This phase includes the Case-Based Reasoning algorithm (CBR) and an optimization algorithm to decide the best action a (configuration set of the radio parameters). By using the link to KB, CBR fetch the previous a (configuration parameters) under environmental state,which is similar to st (from phase one). The configuration parameters a are: the transmit power P_D, modulation scheme M, packet length L and the candidate channel f_C. Also, this phase includes the exchange of a between UE_Ds.

3. Phase 3: Data communication which involves applying the proposed configuration set to the UE_Ds, data transmission, and observing the link response, which depends on the number of Acknowledgment (ACK) and Negative ACK (NACK). These

totally depend on cellular user activity over f_C. In case of link failure (e.g. NACK), this phase sends a request to phase one to start a new link adaptation process. Also, this phase includes learning process to learn (from the link response) the influence of the applied a on the performance of the system using an on Q-Learning (QL) based algorithm. This algorithm updates the quality of the applied action q and reward rwd of the selected configuration set in KB of phase two (more details are in Subsection 5.5.3).

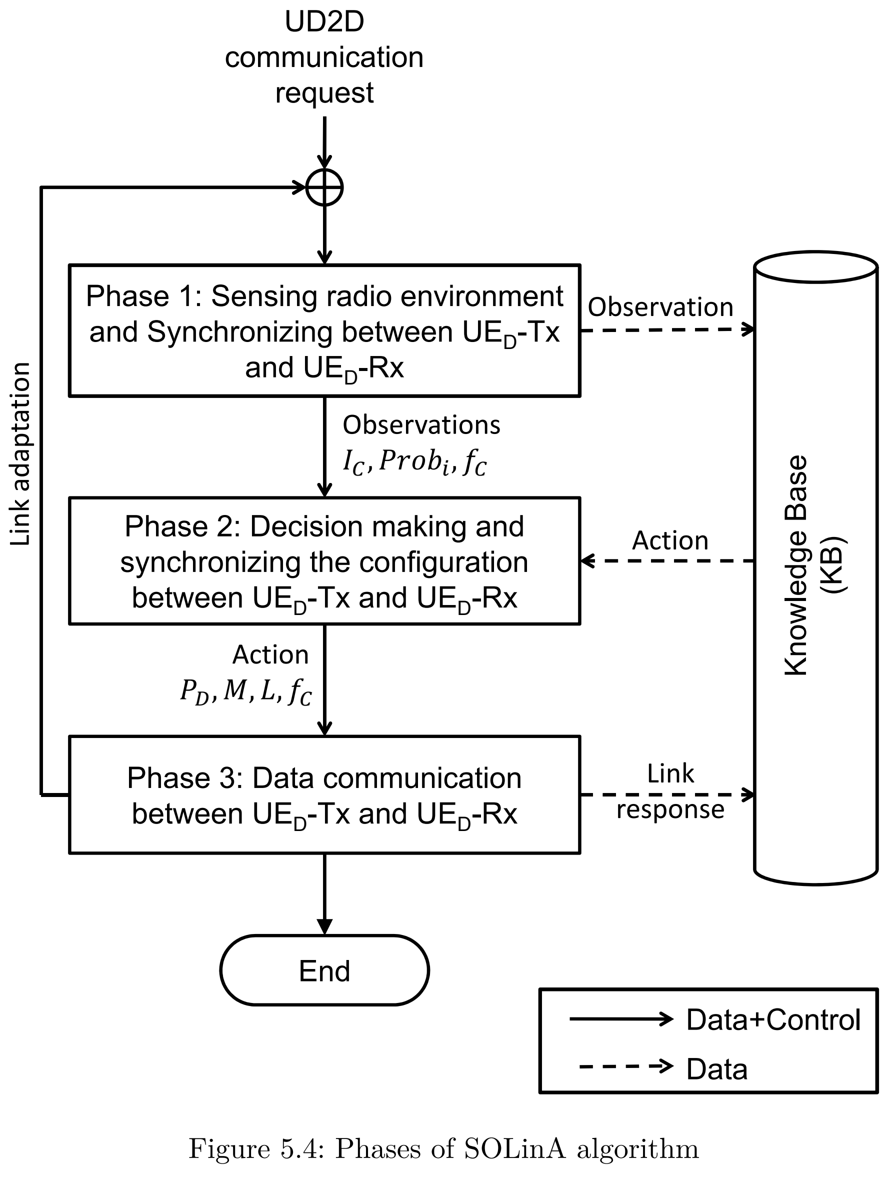

Figure 5.4: Phases of SOLinA algorithm

While any change in the cellular activity generates interference I_C at the $\mathrm{UE_D}$-Rx and could potentially have a negative impact on Γ, there is need to select a sub-channel (which is equivalent to sub-carrier) which has low user activity as well as low I_C. Thus, the $\mathrm{UE_D}$-Rx can perform decision making and learning in order to determine the configuration which minimizes I_C as well as selects the sub-channel with less user activity. However, the $\mathrm{UE_D}$-Tx initiates the communication and can determine P_{Dmax}, as well as defining R_{bth} and BER_{th} for the UD2D communication. To integrate the observation from $\mathrm{UE_D}$-Tx and the configuration from the $\mathrm{UE_D}$-Rx, there is a need to include a two-way handshaking protocol (e.g RTS/CTS mode like in IEEE 802.11 MAC) between the $\mathrm{UE_D}$-Tx and $\mathrm{UE_D}$-Rx, which makes SOLinA algorithm a distributed computation method. The exchange of observations and the configuration between the communication pair using the proposed algorithm is shown as a message sequence chart in Fig. 5.5.

In the following sub-sections, SOLinA phases are explained in detail.

5.5.1 Phase One: Sensing Radio Environment

This phase starts with the following events: i) a data transmission request from the user application; ii) a detected change in the radio environment (such as f_C becoming busy); and iii) when the QoS of the link has been degraded during the transmission process.

The sides of $\mathrm{UE_D}$ pair collect their environmental observations and start the handshaking process to exchange their observations and link configuration. This phase involves the following steps:

1. **Determining the Upper Bound of Transmit Power.** When a transmission request is received, the $\mathrm{UE_D}$-Tx starts observing its radio environment by determining its upper bound of transmit power $P_{D_{max}}$ according to Eq. 3.4.

2. **Requesting Link Establishment.** After determining $P_{D_{max}}$, the $\mathrm{UE_D}$-Tx sends a frame to the $\mathrm{UE_D}$-Rx for requesting link establishment/adaptation. This frame is called ReQuest Link Establishment (RQLE), and is sent via Common Control Channel (CCC). The RQLE frame is an extended version of the Request To Send (RTS) frame, which contains the estimated value of of $P_{D_{max}}$, the QoS requirements (BER_{th} and R_{bth}), in addition to other fields in RTS frame (IEEE 802.11) as shown in Fig. 5.6.

   After sending RQLE frame to the $\mathrm{UE_D}$-Rx, the $\mathrm{UE_D}$-Tx enters a wait state for a limited time until it receives a Clear to Link Establishment (CLE) frame from the $\mathrm{UE_D}$-Rx, which contains the radio parameters to apply.

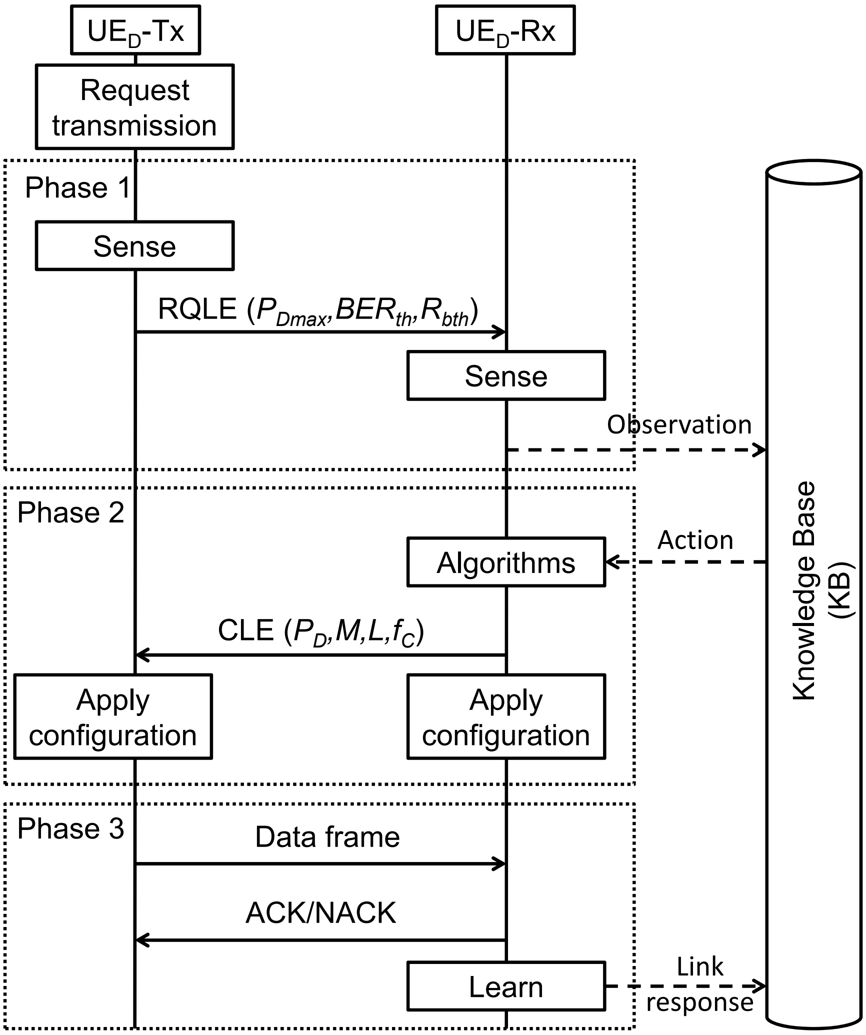

Figure 5.5: Message sequence chart of SOLinA algorithm

3. **Observing Radio Environment at $\mathbf{UE_D}$-Rx.** After receiving RQLE frame in CCC, the UE_D-Rx observes the radio environment on its side using spectrum sensing method. The UE_D-Rx senses the spectrum to determine the activities over each sub-channel f_C.

   At each f_C, UE_D-Rx sensed SS_C which is used to derives the busy time set t_c^b and idle time sets t_c^i in sensing period N samples (the period N is multiple the number of assigned time slot to the UE_C which varies according to the applied cellular system such as GSM, UMTS and LTE) so as to determine the BUSY period samples N_b and the IDLE period samples N_i, as shown in Fig. 5.7 [NCDN13].

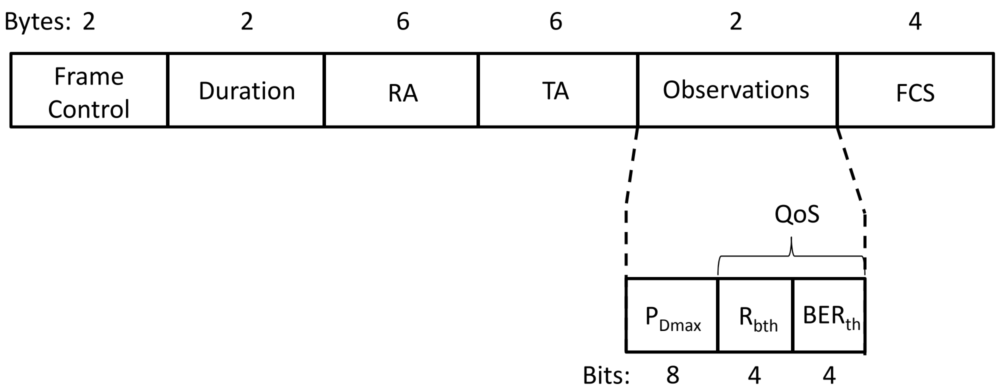

Figure 5.6: RQLE frame format

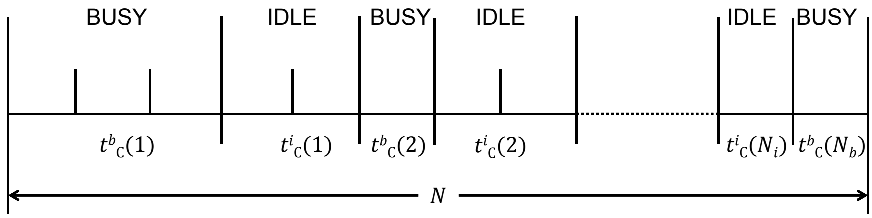

Figure 5.7: Sensing model [NCDN13]

The mean busy time α_C and idle times β_C at f_C are [LA08, NCDN13]:

$$\alpha_C = \frac{1}{N_b} \sum_{j=1}^{N_b} t_c^b(j) \tag{5.1}$$

$$\beta_C = \frac{1}{N_i} \sum_{j=1}^{N_i} t_c^i(j) \tag{5.2}$$

Thus, the probability of f_C being Busy $Prob_b$ is:

$$Prob_b = \frac{\alpha_C}{\alpha_C + \beta_C} \tag{5.3}$$

And the probability of f_C being idle $Prob_i$ is:

$$Prob_i = \frac{\beta_C}{\alpha_C + \beta_C} \tag{5.4}$$

While the SS_C has a dynamic feature, the UE$_\mathrm{D}$-Rx uses energy detection method the derive the average interference I_C by performing sensing for N samples at f_C:

$$I_C = \frac{1}{N}\sum_{i=1}^{N} SS_{Ci} \tag{5.5}$$

Thus, for sub-channel f_C the UE_D-Rx determines the average interference I_C and $Prob_i$ for N samples. By determining these for each sub-channel at UE_D-Rx and P_{Dmax} at the UE_D-Tx, it becomes ready to determine the configuration of the radio parameters.

5.5.2 Phase Two: Decision Making

Configuring the link in SOLinA algorithm is performed using three entities: i) CBR, which is used to exploit past radio parameters (the experience) in a form of state-action pairs for future states to speed up the convergence; ii) Cross-Layer Optimization (CLO) entity, which generates the radio parameters in different OSI layers which achieve desired link objectives (e.g. high throughput and low energy consumption) under certain environmental observations; and iii) exchanging the link configuration between the UE_Ds. SOLinA algorithm runs CBR and CLO at the UE_D-Rx side.

5.5.2.1 Case-Based Reasoning

Reasoning is one of the expert system methods which can be used to perform fast decision making for CR under radio environment with repeated manner. CBR saves some expected observations (cases) and the corresponding radio parameters (actions) and the quality of the applied action at KB in form of case-action-quality entry [MAM+14]. Each entry consists of three parts: i) state $st \in ST$ (f_C^{st}, I_c^{st} and $Prob_i^{st}$); ii) the applied action $a \in A$ (includes P_D, M, L), and iii) the quality of the applied action $qu \in QU$ (fitness value f_t, reward rwd, quality of UD2D link q), as shown in Tab. 5.1. The CBR saves the mean values P_D and M over the sub-carriers in order to apply a unique modulation scheme with a mean power that achieves the desired QoS requirements at each sub-carrier.

The fitness value f_t is computed using fitness function to find how much the action a is suitable with the state s to achieve the desired QoS requirement (more details are explained in Section 5.5.2.2). While the reward rwd is computed in learning entity to find how much the sub-channel f_C behavior is suitable with action a (depends on the response to a and the user activity). The quality q is also computed using learning entity to find the quality of the action a in respect to f_t and rwd. More details about computing rwd and q are explained in Section 5.5.3.

Table 5.1: Knowledge Base

ST			A			QU		
f_C	I_C	$Prob_i$	P_D	M	L	f_t	rwd	q

For each f_c from the observations, the CBR searches for similar f_C^{st} in KB and compute the similarity between the current observations and the saved observations in the KB. The applied CBR uses a similarity function S which determines the most similar previous cases in the KB s^{st} (which includesf_C^{st}, I_C^{st} and $Prob_i^{st}$) to the current sensed radio environment s^c (which includes f_C, I_C and $Prob_i$), so as to pick the proper action a from past cases and apply it to the $\mathrm{UE_D}$ platform. To find the similarity of state s^{st} to current state s^c correctly, both f_C and f_C^{st} should be for the same channel in order to compare other entities. Thus, the s can be performed only within the following condition:

$$\textbf{IF } f_C = f_C^{st} \textbf{ THEN} \text{ compute } S_{st} \tag{5.6}$$

The similarity S_{st} between the s^{st} state in KB and the current state s^c is:

$$S_{st} = 1 - \sqrt{(\bar{I_c} - \bar{I_c^{st}})^2 + (Prob_i - Prob_i^{st})^2}, \tag{5.7}$$

where $\bar{I_c}$ and $\bar{I_c^{st}}$ are normalized values of I_c and I_c^{st}.

After determining S_{st}, CBR selects the best action a_b which has the maximum q.

However, if $S_{st} < S_{th}$ between the states in KB and the current state, the CBR sends the s^c to CLO and trigger signal. Then, the CLO determines a new configuration of the radio parameters. Figure 5.8 shows a flowchart of CBR algorithm.

Depending on S_{st}, phase 2 produces the configuration a either from CBR or CLO and applies it at the radio front ends of both $\mathrm{UE_D}$-Tx and $\mathrm{UE_D}$-Rx. Figure 5.9 shows a state diagram of the integration between CLO and CBR in phase two of SOLinA algorithm at the $\mathrm{UE_D}$-Rx side.

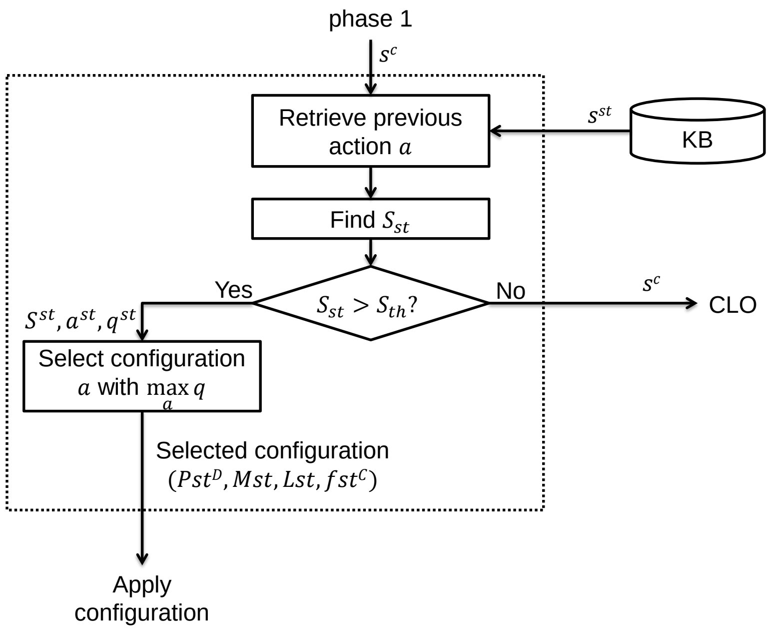

Figure 5.8: CBR

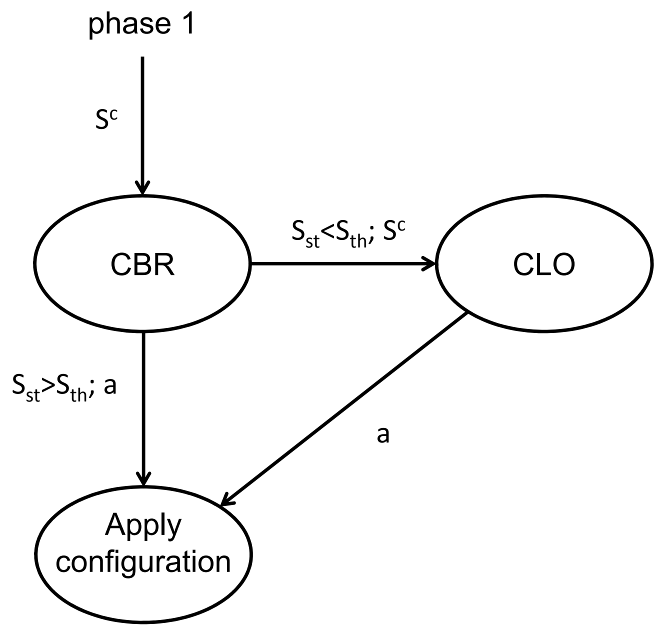

Figure 5.9: State diagram of the integration between CBR and CLO in phase 2 of SOLinA algorithm

5.5.2.2 Cross-Layer Optimization (CLO)

The radio system optimizes its performance by adapting it radio parameters according to the QoS requirements and link objectives in order to meet the desired QoS requirements. However, due to numerous dependencies between the operating parameters and the link objectives of the system, adapting radio parameters becomes as MOOP [NBW+07]. To solve this problem, CLO has been proposed as an approach in wireless systems to coordinate the radio parameters at different layers, with the end goal of achieving the best network performance [SCAL11]. CLO has been proposed to maintain the objectives associated with different layers of OSI model, and to maintain the coordination, interaction, and joint optimization of protocols crossing different layers [ZSV11].

Fitness Functions

The fitness function is a particular type of objective function to summarize how close a given radio parameters set is to achieving the desired link objective [HFWZ12]. The goal of fitness function is to guide the system to one optimal parameter set by computing the fitness value based on a model [MLH+05, New08].

In this dissertation, two fitness functions (related to PHY and MAC layers) are used to represent the optimization goals:

1. Maximizing throughput f_T: This fitness function computes how much throughput does the proposed configuration can achieve based on a model in [New08], to the maximum throughput. This fitness function increases the rate of successful useful data delivery through optimization process. The [New08] proposed a formula to compute the fitness value of the throughput depending implicitly on P_D and M and explicitly on L. However, they considered a single sub-channel with no $\mathrm{UE_C}$'s activity.

   While the sub-channel states (ON and OFF) have a direct impact on the throughput (high ON periods leads to high number of spectrum handover of UD2D communication which reduces the throughput). In this dissertation, the f_T in [New08] has been reformulated in this dissertation to include $Prob_i$ of sub-channel f_C as follows:

$$f_T = \frac{Prob_i \left(\frac{L}{L+\mathrm{Ov}}\right)(1 - FER)\ R_b}{\left(\frac{\mathrm{L_{max}}}{\mathrm{L_{max}}+\mathrm{Ov}}\right) R_{b_{max}}}, \tag{5.8}$$

where $\mathrm{L_{max}}$ is the maximum packet length, Ov is the overhead, FER is the Frame error rate, R_b is the bit rate, and $\mathrm{R_{b_{max}}}$ is the maximum bit rate.

FER and R_b are computed as follows:

$$R_{b_{max}} = \log_2(M_{max})\mathrm{R_{si}N_{sc}}$$

$$R_b = \sum_{i=1}^{\mathrm{N_{sc}}} \mathrm{R_{bi}}$$

$$R_{bi} = \log_2(M_i)\mathrm{R_{si}}$$

$$FER = 1 - \left(1 - \bar{P_{ber}}\right)^{(L+\mathrm{Ov})}$$

$$\bar{P_{ber}} = \frac{1}{N_{sc}} \sum_{i=1}^{N_{sc}} P_{ber_i}$$

$$P_{ber_i} \approx \begin{cases} 2Q\left(\sqrt{\frac{2E_{bi}}{N_o}}\right)^1 & \text{if } M_i == 2 \\ 2Q\left(\sqrt{\frac{2E_{bi}}{N_o}} \sin \frac{\pi}{M_i}\right) & \text{if } M_i > 2 \end{cases}$$

$$\frac{E_{bi}}{N_o} = \Gamma_i.\left(\frac{\mathrm{W_i}}{R_{bi}}\right)$$

$$\Gamma_i = \frac{P_{Di}\ d_D^{-\gamma}}{I_{ci} + \sigma_{n,i}}$$

$$I_{ci} = \frac{I_c}{N_{sc}}$$

$$P_{Di} = \frac{P_D}{N_{sc}}$$

where $\mathrm{N_{sc}}$ is number of sub-carriers, P_{Di} is the transmit power of $\mathrm{UE_D}$ in i^{th} sub-carrier, $\bar{P_{ber}}$ is mean BER, $\mathrm{R_{si}}$ is the symbol rate of i^{th} sub-carrier, $\mathrm{M_{max}}$ is the maximum modulation index, M_i is the modulation scheme in i^{th} sub-carrier, R_b is the achievable bit rate, $\bar{P_{ber}}$ is the probability of achievable BER, P_{ber_i} is probability of BER in i^{th} sub-carrier, $\frac{E_b i}{N_o}$ is energy per bit to noise spectral density ratio in i^{th} sub-carrier, $\mathrm{W_i}$ is the bandwidth of i^{th} sub-carrier, Γ_i is the achievable UD2D SINR of i^{th} sub-carrier, $\sigma_{n,i}^2$ is the noise power of i^{th} sub-carrier, I_{ci} is the cellular interference of i^{th} sub-carrier, and P_{ri} is the power received in i^{th}

[1] $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp(\frac{-t^2}{2})dt$

[1] $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp(\frac{-t^2}{2})dt$

sub-carrier.

The throughput over the sub-channel f_C depends on FER which reflects the average BER P_{ber} over the sub-carriers. Each P_{beri} depends mainly on Γ_i which is influenced negatively by the cellular interference portion I_{Ci}. Thus, the CLO needs to find the possible P_{Di} and M_i which degrades the P_{beri} at the i^{th} sub-carrier.

2. Minimizing energy consumption f_E at the transmitter. This function is based on the amount of P_D to the maximum transmit power of the $\mathrm{UE_D}$-Tx[NRW+07]. The P_D depends on the sum of P_{Di} per each sub-carrier:

$$f_E = 1 - \left(\frac{1}{N_{sc}} \frac{\sum_{i=1}^{N_{sc}} P_{Di}}{\mathrm{P_{D_{max}}}} \right), \tag{5.9}$$

where P_{Di} is the transmit power at i^{th} sub-carrier.

To perform the CLO efficiently with aggregated fitness functions, weighted sum approaches is applied in this dissertation to sum the positively normalized weighted scores of each single fitness function and compute the global system performance [dBMP08]. Thus, the total fitness function of the system f_t is:

$$f_t = w_1 f_T + w_2 f_E, \tag{5.10}$$

where the weights (w_1, w_2) are defined as a policy of the link state in which $\sum_{i=1}^{2} w_i$ =1.

Constraints

To optimize the performance of any wireless system, some constraints should be defined which represent the system regulatory bounds, limitations in the hardware of $\mathrm{UE_D}$s and the desired QoS requirements of user application. In this dissertation, the applied constraints are classified into two classes:

1. Cellular constraint which is related to the performance of the BS Γ_C. According to Eq. 3.4, the $P_{D_{max}}$ is the upper bound of interference-free transmit power of $\mathrm{UE_D}$s.

2. $\mathrm{UE_D}$ constraints which are related to the performance of UD2D communication. These constraints are:

- Threshold data rate $R_{b_{thr}}$:
$$R_b \geq R_{b_{thr}} \tag{5.11}$$
- The channel capacity of $\mathrm{UE_D}$:
$$R_b \leq N_{sc} W_i \log_2 \left(1 + \Gamma_i\right) \tag{5.12}$$
- Threshold Bit Error Rate BER_{thr}
$$P_{ber} \leq BER_{thr} \tag{5.13}$$
- Packet transmission time:
$$\frac{L}{R_b} \leq T_s, \tag{5.14}$$
where T_s is the time slot.

Adaptive Discrete Particle Swarm Optimization (ADPSO) Algorithm

Different heuristic-search algorithm have been used to perform CLO. In [CNEW10, dBMP08, NBW$^+$07], the authors proposed GA to optimize the radio parameters under dynamic radio environment. While the authors in [ZXZS09] proposed a Discrete form of PSO (DPSO) algorithm for optimizing the radio parameters. However, both GA and PSO suffer from issues such as: i) slow convergence, which negatively affects the link adaptation process in CR under real time scenario, and ii) local optima problem in which the optimization algorithm becomes unable to discover a new region in the search space that can yield better fitness value.

To reduce the impact of local optimum and speed-up the searching process, a new version of PSO-based algorithm is proposed in this dissertation called Adaptive Discrete PSO (ADPSO) to conquer the aforementioned drawbacks of the applied algorithms in previous work [MMKMT12]. The ADPSO is running as a CLO algorithm inside ($\mathrm{UE_D}$-Rx) within phase 2 of SOLinA algorithm. The measurements of the peer node ($\mathrm{UE_D}$-Tx) are merged with ($\mathrm{UE_D}$-Rx) at phase 1 of SOLinA algorithm to get the environmental observations. Then, ADPSO used them to find the configuration set a which meets the desired QoS.

To explore the search space efficiently, the search process must be repeated until the stopping criteria is reached. This is represented by the number of iterations T. Figure 5.10 shows a flowchart of ADPSO algorithm.

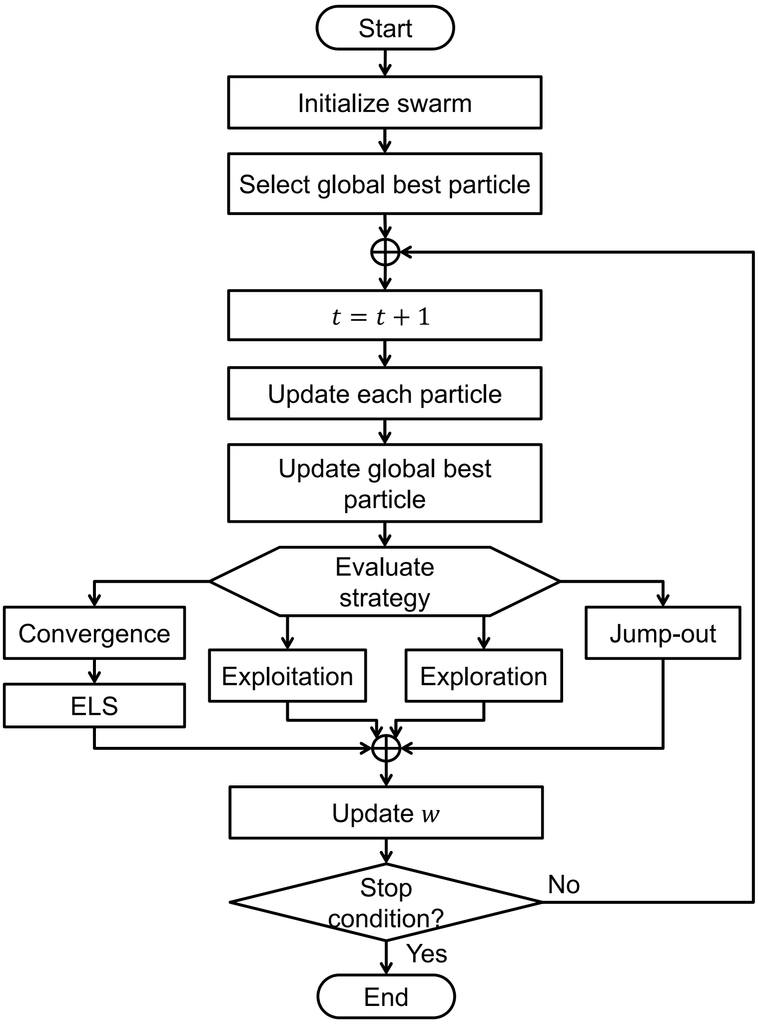

Figure 5.10: Flowchart of ADPSO algorithm

1. **Initiate swarm**
   In the first step of ADPSO, the swarm is generated by set of particles. Each particle X represents a set of radio parameters to be optimized. Each radio parameter at X is selected randomly within its upper and lower bounds. The arrangement of each X will be as follows:

$$X = [P_{D_1}, M_1, P_{D_2}, M_2, ..., P_{D_{N_{sc}}}, M_{N_{sc}}, L, f_C]$$

2. **Select the global best particle**

Table 5.2: Modification of self-confidence and swarm confidence values

Strategy	Range of $gBest^t$	c_1	c_2
Jump-out	$0 \leq gBest^t$ <0.2	-0.1	+0.1
Exploration	0.2$\leq$ $gBest^t$ <0.4	+0.1	-0.1
Exploitation	0.4$\leq$ $gBest^t$ <0.6	+0.05	-0.05
Convergence	0.6$\leq$ $gBest^t$ <1.0	-0.05	+0.05

ADPSO computes the fitness value f_t of each particle, which is determined by using Eq. 5.10. Then, ADPSO selects the global best $gBest^t$ of the swarm according to the maximum f_t in the swarm:

$$gBest^t = \max_{X_j} f_t, \tag{5.15}$$

In addition, each particle saves its local best position $lBest_j^t$, which is the position with the best fitness found so far for particle j at iteration t. However, the iteration at this step is $t = 0$.

3. **Repeat until the stopping criterion:**

   a) **Update particles**
   The basic process of updating particles involves updating the velocity of each particle according to the positions of the $gBest^t$, then using the particle's' velocity to update the position of the particle [KE95].

   b) **Update global best particle**

   After updating each particle, the one with maximum f_t is selected as a temporary global best particle. Then, it is compared to the previous global best one at $t-1$, and the ADPSO selects the one with the maximum f_t as the global best particle at t.

   c) **Decide searching strategy** In order to improve the performance of searching process in PSO-based algorithm, four different searching strategies (jump-out, exploration, exploitation, and convergence), ADPSO can adapt its coefficients (self-confidence c_1, swarm confidence c_2 and inertia weight w) according to each search strategy in order to speed-up the searching process [ZZLC09]. The ADPSO adapts the values of c_1 and c_2 according to $gBes^t$, as shown in Table 5.2.

   To avoid falling in a local optima regions, Elitist Learning Strategy (ELS) is applied in ADPSO to $gBest^t$ so as to search for another region, which avoids local optima regions. The authors in [ZZLC09] proposed a jumping-out mechanism to enhance the search algorithm by helping the global best particle to jump-out of local optima regions during a convergence strategy. The procedure of ELS is:

- Randomly select one dimension of $gBest^t$:

$$n = random\,(1, N) \tag{5.16}$$

$$Tmp = gBest^t$$

- Update the parameter of the selected dimension value $gBest^t(d)$ as follows:

$$Tmp^n = Tmp^n + (UB\,(Tmp^n) - LB\,(Tmp^n)) \times Gaussian\left(\mu, \sigma^2\right) \tag{5.17}$$

  where $UB(Tmp^n)$ is the upper bound of dimension n, $LB(Tmp^n)$ is the lower bound of dimension n, μ is center of Gaussian and σ is the standard deviation (ELS learning rate). As a training scheme that changes in relation to time, σ is linearly decreased with the iteration number [ZZLC09]:

$$\sigma = \sigma_{max} - (\sigma_{max} - \sigma_{min}) \times t/T$$

  where σ_{max} and σ_{min} are the upper and lower bounds of the learning scale.

- Update Tmp with the value of Tmp^n at dimension n.
- Compute f_t of Tmp and compare it with the fitness value of $gBest^t$:

$$gBest^t = \begin{cases} Tmp & \text{if } f_t(Tmp) > f_t(gBest^{t-1}) \\ gBest^{t-1} & \text{elsewhere} \end{cases}$$

  In case where Tmp has less f_t than $gBest^{t-1}$, Tmp replace the particle with the minimum f_t in the swarm at iteration t.

d) **Select the global best particle at the final iteration**
In order to find best solution in ADPSO, the search process must be repeated until the stopping criteria is reached. This criteria can be reached in different

manners:

- Define a goal of QoS requirements in which the ADPSO stops whenever it this goal is meet.
- Convergence is achieved due to no change in f_{total} for a certain number of iterations.
- Define a certain number of iterations T in which the ADPSO stops its search when the T is reached.

In this dissertation, the stop criteria depends mainly on achieved convergence. However, in case of no convergence, the search stops after T iterations.

5.5.2.3 Exchanging Configuration Set

After determining the set of radio parameters that optimizes the performance of UD2D communication, the $\mathrm{UE_D}$-Rx sends a CLE frame that contains the configuration of radio parameters to the $\mathrm{UE_D}$-Tx in order to re-configure its radio parameters, as shown in Fig. 5.11.

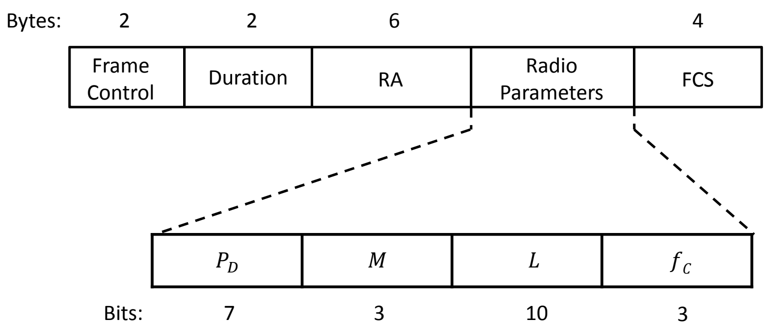

Figure 5.11: CLE frame format

5.5.3 Phase Three: Data Communication

This phase has two parts which work sequentially: data transmission part and learning part.

Data Transmission

After applying the configuration of radio parameters on both communication pair, the $\mathrm{UE_D}$-Tx sends its data frames to $\mathrm{UE_D}$-Rx which checks the frame error by using Frame

Check Sequence (FSC). Then, it replies with ACK or NACK according to the received frame. The frame transmission is continued whenever the UE_D-Tx received ACK. Otherwise, a link adaptation is sent phase one. Meanwhile, updating *rwd* is performed at UED-Rx side. Figure 5.12 shows a atate machine which explains phase 3.

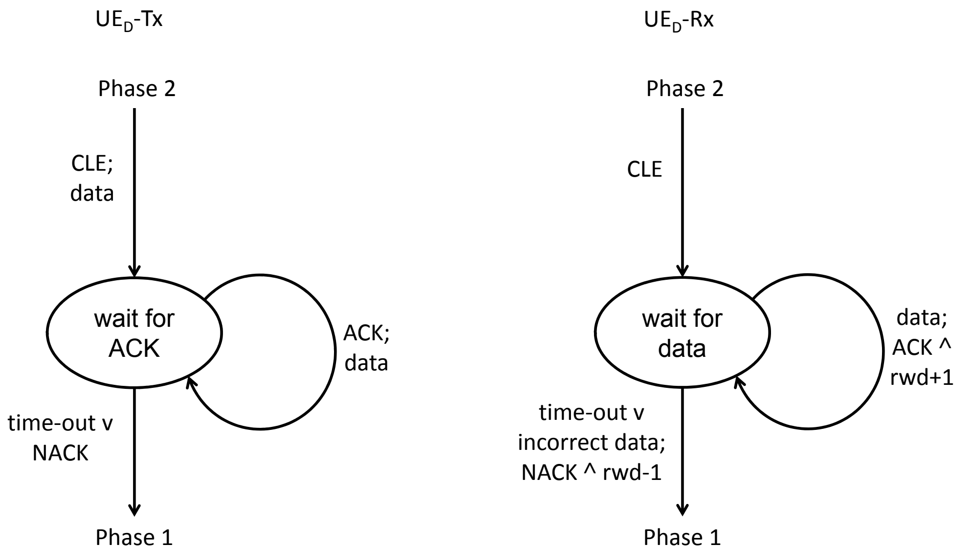

Figure 5.12: Phase 3 of SOLinA algorithm

This phase supports the transmission of more than of data frame, in which the learning process id performed for each received data frame. In case of incorrect data frame or time-out without reception of data frame, phase one will be triggered at both sides (UE_D-Tx and UE_D-Rx), as shown in Fig. 5.13.

Learning

Reinforcement Learning (RL) is a machine learning solution where, through interaction with its environment, an agent learns optimal behavior for certain states of the environment [APB+10].

By using CBR, the UE_D is able to select the best a among a set of past cases st with similar conditions as the observed case. However, each of these a is may be used only once and may not represent the best overall solution in case of significant changes in the radio environment, especially if the cellular activities over sub-channels varies over time and unknown to the UE_D pair.

The goal of learning entity is to learn the behavior of stochastic radio environment (such as UE_C activity) so as to determine the best sub-channel to select, which has more

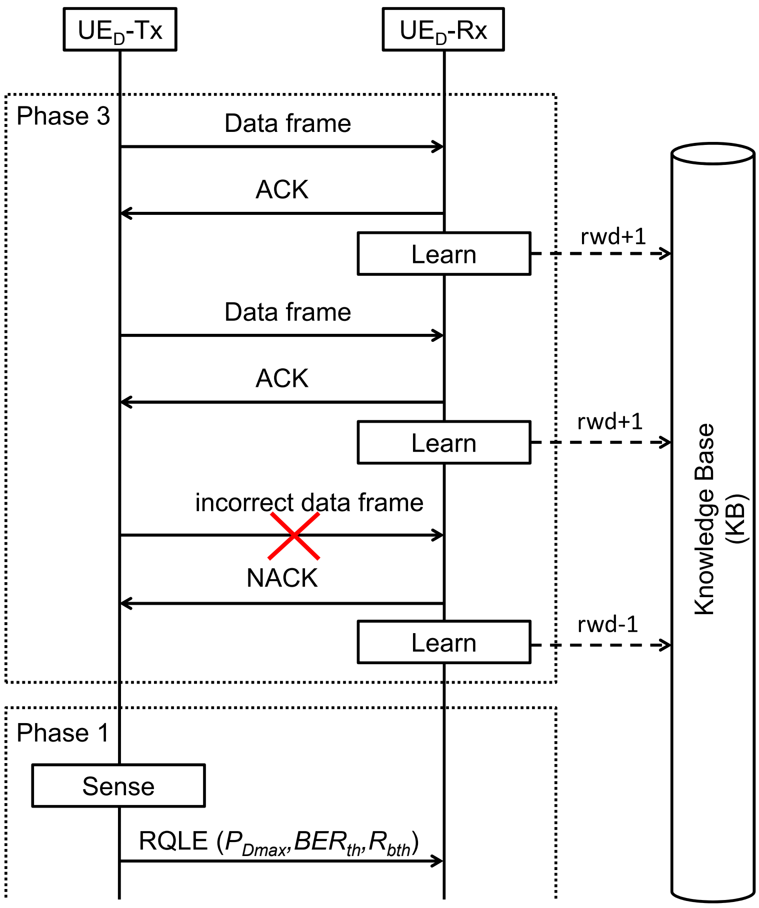

Figure 5.13: Message sequence chart of phase 3 in case of multiple data frames

spectrum holes. The learning entity evaluates the performance of a in CBR according to cellular activities (how many times each sub-channel is free to access) and the link status (number of link failure). By evaluating the quality of a according to f_t, cellular activity and link failure, the decision making will have a clear view about each configuration of radio parameter (P_D, M, L and f_C) at each case st in order to find the best configuration to apply.

In the traditional Q-L model, learned value includes the estimated future performance, which is obtained through fixed states. However, in the predefined system model in Section 5.1, the states do not estimate the future of the link due to the influences I_C and $Prob_i$ at each f_C.

Thus, a Modified Q-Learning model (MQL) is applied in this dissertation. The $q \in qu$ ($qu \in QU$) represent the quality of UD2D link when applying $a \in A$ under $st \in ST$.

The q value is related to: i) the reward rwd (performance history) of the link using a, ii) the q^t which describes the quality of applying a under st. By utilizing the information of f_t and performance history the learner can make better decisions about sub-channel selection and the configuration of radio parameters.

At time instant t for each case st with applied action a^{st} (in CBR), the MQL updates its reward rwd_a^t according to the number of successful transmitted packets using a^{st}

$$rwd_a^t = \begin{cases} rwd_a^{t-1} + 1, & \text{ACK} \\ rwd_a^{t-1} - 1, & \text{NACK/Hand-off} \end{cases} \tag{5.18}$$

The indication of Hand-offs occurs if two successive time slots of selected sub-channel f_C are busy.

By updating the rwd_a^t after each successful transmitted packet, the MQL updates the q_a^t of action a^{st} as follows:

$$qu_{(st,a)}^t = (1-\alpha)f_t + \alpha \frac{rwd_a^t}{NrAck} \tag{5.19}$$

where $NrAck$ is the number of ACK frames sent by $\mathrm{UE_D}$-Rx, f_t is the fitness value of action a under case st, and α is the learning rate ($\alpha \in [0,1]$). Figure 5.12 shows learning process at phase 3.

5.6 Summary

In this chapter, a self-organizing algorithm for link adaptation has been proposed to conquer the challenges related to the radio environment. The proposed algorithm is a hybrid based on merging three different entities, each represents a technique to solve specific challenge. Optimization entity is based on ADPSO algorithm which applies heuristic search to find radio parameters set which optimize the UD2D link under environmental observations and QoS requirements. The ADPSO is proposed to conquer the local optima problem by searching different positions in the search space to find a set of radio parameters which achieves better performance (i.e higher fitness value). The reasoning entity memorizes the previous actions and applies them at current states using CBR algorithm. The usage of CBR reduces the computational efforts and speeds-up the convergence of the system. The learning entity applies MQL to learn the behavior of each channel and the impact of the applied action on the performance of the UD2D communication link.

The SOLinA algorithm merges these entities to form an algorithm which applies self-organization in UD2D communication to adapts its link efficiently in autonomous way. Applying self-organization features in UD2D communication improves its performance and conquer the challenges of the radio environment. In order to evaluate the performance of the proposed algorithm, a simulation scenario of UD2D communication has to be performed under dynamic radio environment in order to study the behavior of UD2D communication link under such environmental behavior.

6 Simulation and Evaluation of UD2D Link Performance

Contents

This chapter introduces the simulation scenario for UD2D link adaptation. The simulation assumptions are presented. The models of path loss, propagation and interference which have been used in the simulation are explained in details. Then, the results are discusses with the evaluation of the applied algorithms. Later, the conclusion is presented.

6.1 Simulation Scenario

The simulation scenario consists of stationary pair of UE_Ds and a number of UE_Cs in a macro-cell which has a frequency reuse factor of 1, as shown in Fig. 5.1. The UE_Ds use the UL sub-band to perform UD2D communication. The UL sub-band is divided into a number of sub-channels f_C with a bandwidth W_C. Each f_C is divided (in time

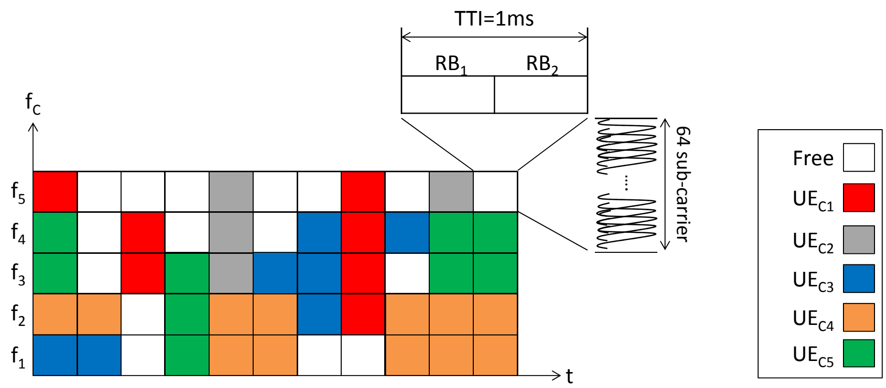

Figure 6.1: $\mathrm{UE_C}$ activities over UL sub-channels

dimension) into time slots to form RBs which are allocated by BS to $\mathrm{UE_C}$s in the CoI. Each sub-channel consists of N_{sc} sub-carriers.

In the cellular system, the BS allocates RBs in UL sub-band for the $\mathrm{UE_C}$s for their transmissions according to the CSIs which are sensed by the $\mathrm{UE_C}$s and collected by the BS. When the $\mathrm{UE_D}$s attempt to perform UD2D communication, they sense the UL sub-band for N time slots to find the activity over each sub-channel. The sensed sub-channels may have different BUSY periods (duty cycles DC) due to the different gains between the $\mathrm{UE_C}$s and $\mathrm{UE_D}$ over the sub-channels, traffic at each $\mathrm{UE_C}$ and the P_C used to perform cellular communication. The sub-channels with shorter DCs (less $\mathrm{UE_C}$'s activities) have more spectrum holes with wide size, compared to others with longer DCs, as shown in Fig. 6.1. The $\mathrm{UE_C}$s are located close to each other to have similar distance to the BS and the $\mathrm{UE_D}$s which makes the P_C and the d_{CD}^{γ} over each sub-channel equal between all $\mathrm{UE_C}$s and $\mathrm{UE_D}$-Rx. This makes traffic over each sub-channel as the only difference between the sub-channels which can be sensed by using spectrum sensing. Thus, the learning entity in SOLinA algorithm needs to learn which sub-channel has less $\mathrm{UE_C}$s activities in order to use its spectrum holes for UD2D communication. The simulated scenario considers that the BS distributes the RBs over the sub-channels not equally due to some sub-channels which have CSIs with low quality. Thus, these sub-channels have less cellular activities (more spectrum holes) which enable the $\mathrm{UE_D}$ pair to perform UD2D communication over them.

The $\mathrm{UE_D}$ pair tries to perform UD2D communication to transfer data of specific size with the minimum latency, maximum goodput, and minimum signaling overhead. To study the influences of geographical positions of cellular entities and their QoS requirements on the performance of the UD2D communication, the $\mathrm{UE_D}$ pair establishes a direct communication at different positions in the cell.

6.2 Simulation Assumptions

To evaluate the performance of UD2D communication link using the proposed algorithm, a simulation has been performed based MATLAB simulator. Table 6.1 presents the simulated parameters related to cellular network, UD2D communication and SOLinA algorithm. Different models related to the radio environment have been applied in the simulation scenario to achieve a dynamic radio environment. In the next subsections, the details of the applied models in the simulation are presented.

6.2.1 Path Loss Model

Path loss represents the power loss of the propagated signal in the transmission range. The path loss PL has been modeled as in Section 3.5.1. The shadowing effect has been modeled as a Gaussian distribution with mean μ of zero and standard deviation of σ ($\mathcal{N}[0, \sigma]$).

6.2.2 Propagation Model

The propagation model represents the change in the signal power from the transmitter to the receiver in the wireless system. The model accounts all the gains and the losses in the simulation scenario of wireless system. The propagation model is similar to Eq. 3.64. By applying Eq. 3.2 and 3.4 in Eq. 3.64, the received power at BS P_{r_C} and at $\mathrm{UE_D}$ P_{r_D} are:

$$P_{r_C} = 10\log_{10}\left(k\Gamma_C\sigma_n^2 d_C^\gamma\right) + A_{UE} + A_{BS} - PL_C \tag{6.1}$$

$$P_{r_D} = 10\log_{10}\left((k-1)\sigma_n^2 d_{BSD}^\gamma\right) + A_{UE} + A_{UE} - PL_D, \tag{6.2}$$

where d_C^γ is the path loss between the $\mathrm{UE_C}$ and BS in linear, d_{BSD}^γ is the path loss between the BS and $\mathrm{UE_D}$ in linear, PL_{BSD} is the path loss between the $\mathrm{UE_D}$-Tx and BS [dB], A_{UE} is the antenna gains of UEs (for $\mathrm{UE_C}$, $\mathrm{UE_D}$-Tx and $\mathrm{UE_D}$-Rx) [dBi], A_{BS} is the antenna gain of BS receiver [dBi] and PL_D is the path loss between $\mathrm{UE_D}$ pair [dB].

Table 6.1: Simulation assumptions of UD2D link adaptation

	Parameter	**Value**
Cellular system	Number of sub-channels f_C	[1, 5]
	Number of sub-carriers N_{sc}	64
	Interference margin k (dB)	3
	Cellular threshold SINR Γ_C (dB)	10
	Cell radius R_C (m)	10000
	BS antenna gain A_{BS} (dBi)	10
	UE antenna gain A_{UE} (dBi)	2
	Duty Cycle DC	15%,20%,30%,25%,10%
	noise floor σ_n^2 (dBm)	-110
	Path loss exponent γ	3
	Bandwidth W (MHz)	3
	Shadowing effect sh (dB)	$\mathcal{N}[0,4]$
UD2D	Threshold SINR Γ_D (dB)	7
	P_D (dBm)	[-40, 30]
	Modulation schemes M	BPSK, QPSK, 8-PSK 16-QAM, 64-QAM
	Frame length L (Byte)	[100, 1000]
	Threshold BER BER_{th}	10^{-4}
	Threshold bit rate $R_{b_{th}}$	3.4 Mbps
SOLinA	learning rate α	0.3
	Similarity threshold S_{th}	0.85
	Swarm size SW	30
	Inertia weight w	1.9
	Initial c_1	2.0
	Initial c_2	2.0
	Maximum iteration number T	300
	fitness weights w_1, w_2	0.9, 0.1

6.2.3 Interference Model

The interference generated by UE_C at the UE_D-Rx I_C and the interference generated by UE_D-Tx at the BS I_D are modeled by substituting Eq. 3.2, 3.4 in Eq. 3.64. The I_C and I_D modeled as:

$$I_C = 10\log_{10}\left(k\Gamma_C\sigma_n^2 d_C^{\gamma}\right) + A_{UE} + A_{UE} - PL_{CD} \tag{6.3}$$

$$I_D = 10\log_{10}\left((k-1)\sigma_n^2 d_{DBS}^{\gamma}\right) + A_{UE} + A_{BS} - PL_{DBS}, \tag{6.4}$$

where d_C^{γ} is the path loss between UE_C and BS in linear, d_{DBS}^{γ} is the path loss between the BS and UE_D-Tx in linear, PL_{CD} is the path loss between the UE_C and UE_D-Rx [dB] and PL_{DBS} is the path loss between the UE_D-Tx and BS [dB] .

In the simulation scenario, both I_C and I_D include the shadowing effect sh.

6.2.4 Traffic Model

The BS has allocated for each UE_C number of RBs over each sub-channel to perform its activity. The number of allocated RBs per each sub-channel are different according to its sensed CSIs by the UE_Cs make different average duty cycles DC per each sub-channel. The traffic model at each sub-channel can be modeled in an exponentially distribution form with specific mean value represented by DC [LA08, UN09, NCDN13].

6.2.5 UE_D Specifications

Each UE_D is equipped with two Transceivers (XCVRs). The first XCVR operates on CCC to manage the exchange of observations and the radio parameters between UE_Ds. The second XCVR is used CR to tune to any of the UL sub-channels to perform the sensing, as well as exchanging data packets [KPMT12].

In this dissertation, it is assumed that time required to configure the UE_D pair for the new configuration is neglected from the account. Also the runtime of ADPSO and CBR is also neglected. The counted time is the signalling overhead of RQLE, CLE, ACK, NACK and the sensing time at the spectrum sensing.

6.3 Evaluation

Evaluating the quality of any wireless systems depends on its performance under dynamic radio environmental, in which many time-variant events (such as noise, interference, shadowing, multi-path, etc.) may affect the link quality and make link failure if the QoS requirements are not met. The performance of any communication link is evaluated according to different metrics which are related to the desired QoS requirements of the system, as well as its limitations. One of these metrics which has been studied is the goodput. This metric shows the ratio of useful correctly-received data over a transmission time, which is affected by the environmental behavior, as well as the radio parameters [FNAV08, QCS02].

In this chapter, the goodput of UD2D communication has been studied according to:

1. The distance between $\mathrm{UE_D}$ d_D.
2. The SINR threshold of cellular system Γ_C
3. The impact of positions of $\mathrm{UE_C}$ and $\mathrm{UE_D}$ pair in the cell.

Different heuristic search-based algorithms has been applied in CR technique for link adaptation such as GA and PSO [CNEW10, dBMP08, NBW+07, ZXZS09]. However, the researchers in [ZXZS09, ZPZS09] show that the PSO has outperformed GA while applying it as a link adaptation algorithm in UD2D communication. In this dissertation, UD2D communication has been simulated in the aforementioned metric using two optimization algorithms for link adaptation: PSO and SOLinA algorithms.

6.3.1 The Impact of Distance between $\mathrm{UE_D}$

The distance between the communicated $\mathrm{UE_D}$ pair d_D has impact on the goodput of the communication. This impact varies according to the geographical position of $\mathrm{UE_D}$ pair in CoI due to the distance from both $\mathrm{UE_C}$ and the BS. The relation between the d_D and the goodput have been studied at two different positions in CoI: i) at the cell edge; and ii) at the cell center, as shown in Fig. 6.2. These positions reflects the impact of I_C and I_D between the cellular and UD2D communication.

Figure 6.3 (a) and (b) shows the impact of d_D on the goodput using PSO and SOLinA algorithms for link adaptation at both cell edge and cell center, respectively. The d_D is inversely proportional to the goodput due to the reduction of P_{rD} (with the increase of d_D) which degrades the Γ of UD2D communication.

The goodput at the cell edge is higher than at the cell center due to: i) low influence of BS on P_{Dmax} (the upper bound of P_D is decreased when the d_{BSD} is short); ii) low influence of I_C on Γ (which is increased at positions close to $\mathrm{UE_C}$). Thus, the reduction in P_D, as well as the increase of I_C and PL_D degrade the Γ of the UD2D communication

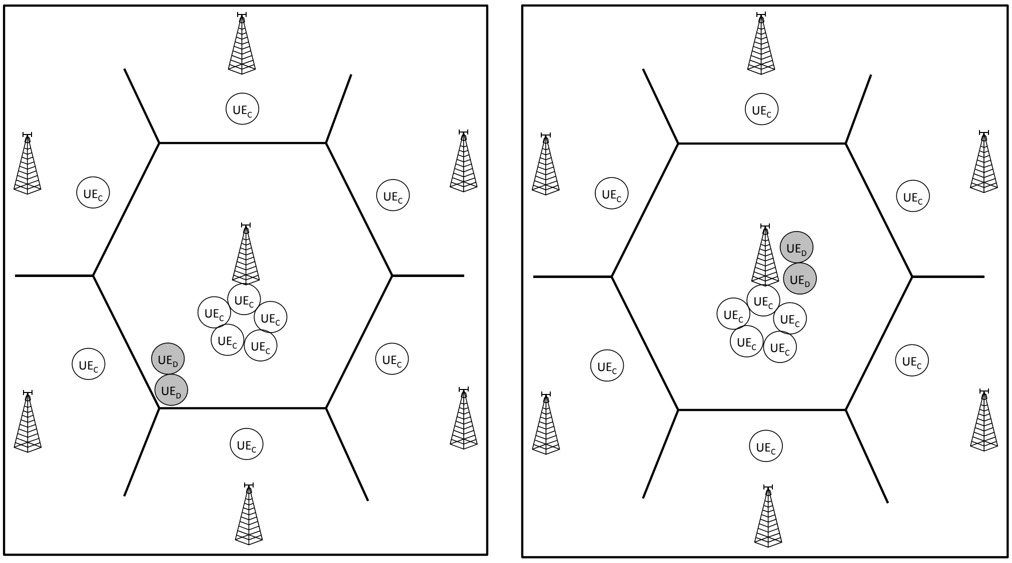

Figure 6.2: Different positions of UE$_\text{D}$ in the cell: (a) cell edge, (b) cell center

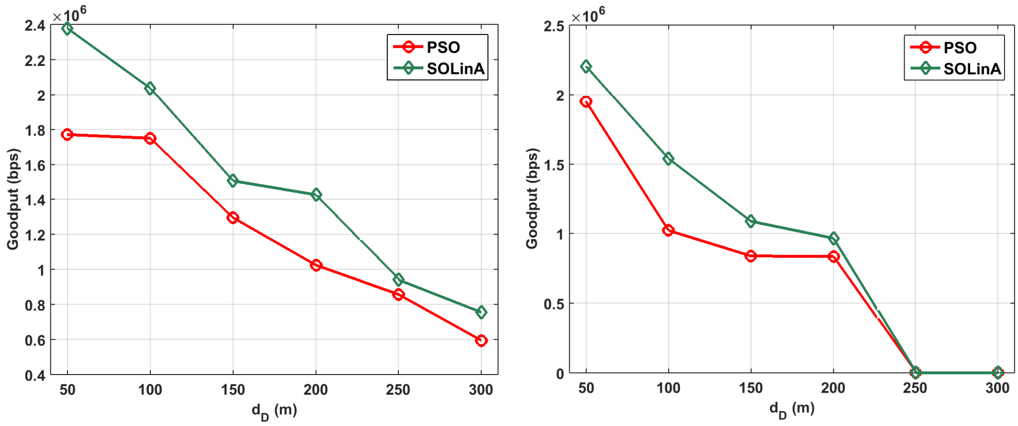

Figure 6.3: The impact of d_D on the goodput of UD2D communication PSO and SOLinA algorithms at different positions of UE$_\text{D}$ in the cell: (a) cell edge, (b) cell center

at cell center, which makes the UE$_\text{D}$-Tx adapts the modulation scheme M (reduces the modulation index) and reduce the packet length L to achieve a low acceptable bit rate with free-error link.

The change in goodput does not dependent only on d_D and the positions, but also on the scheme which configures the link between the UE$_\text{D}$. Figures 6.3 (a) and (b) show that SOLinA algorithm outperforms the PSO algorithm in goodput at both cell edge and cell center. This performance of SOLinA is due to: i) adaptation of optimization

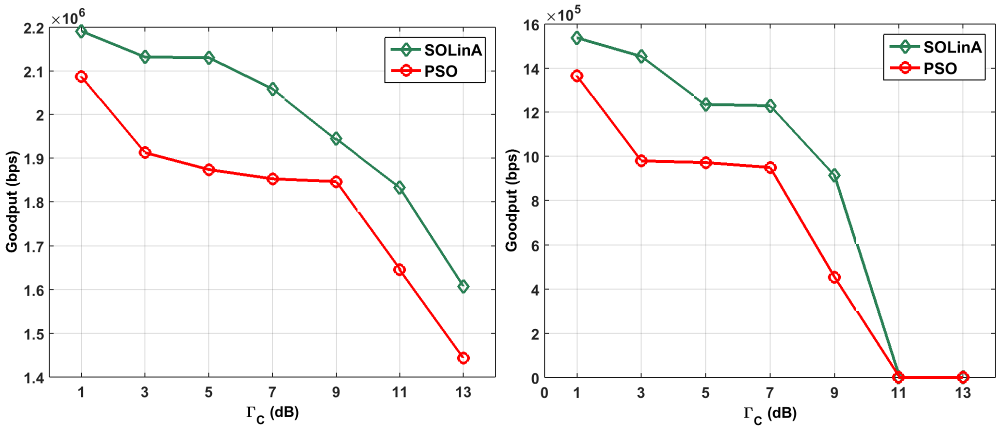

Figure 6.4: The impact of Γ_C on the goodput of UD2D communication PSO and SOLinA algorithms at different positions of $\mathrm{UE_D}$ in the cell: (a) cell edge, (b) cell center

factors (c_1, c_2,and w_i) ; ii) searching strategy which speed-up the search process toward the convergence; iii) the ELS which attempts to search different positions in the search space to conquer the local optima problem (searches for different configuration set); and iv) the MQL learns the best f_C to select, which has the most idle periods. These factors guide SOLinA toward the new regions in the search space with better solution (configuration set) which achieves the higher goodput, compared to PSO algorithm.

6.3.2 The Impact of Cellular SINR

In this subsection, the impacts of Γ_C on the goodput is studied in details at two different positions in cell: i) at the cell edge; and ii) at the cell center, as shown in Fig. 6.2. These impacts varies according on the geographical position of $\mathrm{UE_D}$ pair in the cell which may increase or decrease due to the distance from both $\mathrm{UE_C}$ and the BS.

Figure 6.4 (a) and (b) shows the impact of Γ_C on the goodput of UD2D communication using PSO and SOLinA algorithms at both cell edge and cell center, respectively. The increase in Γ_C decreases the P_D and the Γ of UD2D communication, as in Eq. 3.4. The goodput at the cell edge is greater than at the cell center due to the low negative impact of BS and the $\mathrm{UE_C}$ which increase P_D (as in Eq. 3.6) and decrease I_C (as in Eq. 6.3), respectively. Thus, $\mathrm{UE_D}$-Tx switches to higher modulation scheme (increases M) and increases L for a free-error link which increases the size of transmitted data per time.

Although the Γ_C is inversely proportional to goodput, the achieved value of goodput varies according to the applied scheme for link adaptation. Figure 6.4 (a) and (b) shows that the SOLinA algorithm outperforms the PSO algorithm in goodput at both cell edge and cell center with the increase of Γ_C. This performance of SOLinA is due to: i) adaptation of optimization factors; ii) searching strategy which speed-up the search process; iii) the ELS which attempts to conquer the local optima problem (searches for different configuration set); and iv) the MQL learns the best f_C to select which has the most idle periods. These factors guide SOLinA toward the best solution (configuration set) which achieves the high goodput, compared to PSO algorithm, at different positions in the cell.

6.3.3 The Impact of the Geographical Positions of UE_C and UE_D pair

The geographical positions of UE_C and UE_D pair in the cell have impact on the system capacity, as shown in Chapter 3. In this subsection, the goodput is studied under different positions of UE_C and UE_D pair (in line of sight with the BS) in the cell using PSO and SOLinA algorithm, as shown in Fig. 6.5.

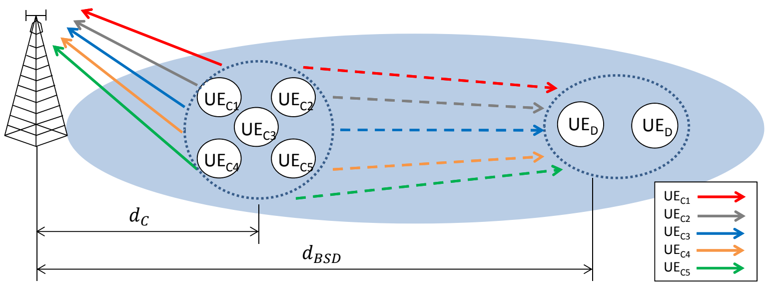

Figure 6.5: Simulation scenario of different geographical positions in UD2D communication

Figures 6.6 (a) and (b) show the achieved goodput of UD2D communication using PSO and SOLinA algorithms, respectively in which the color at each square represents the achieved goodput of UD2D communication at a specific position in the simulation path (certain d_{BSD} and d_C). Most of the high values in goodput occurs when UE_Ds are located at positions close to the cell edge and the UE_Cs are close to the cell center. The general reason behind increment is the high P_D (low impact from BS according to Eq. 3.4), as well as low interference from UE_Cs as in Eq. 6.3. However, the SOLinA algorithm outperforms the PSO algorithm at these positions due to the use of ELS (in ADPSO) which attempts to conquer the local optima by searching different positions in the search space of the radio parameters which leads to achieve higher f_t and improve the goodput.

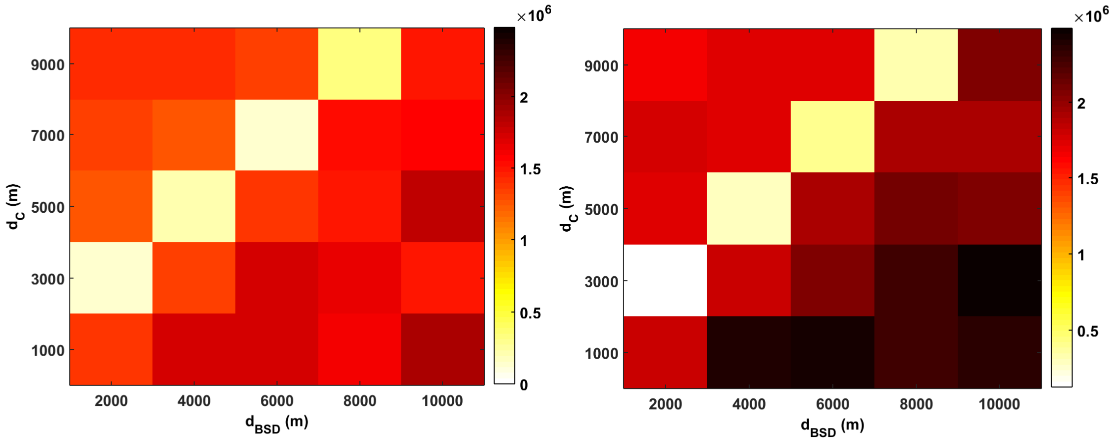

Figure 6.6: Goodput vs. d_{BSD} and d_{BSC} using: (a) PSO-based algorithm, (b) SOLinA algorithm

The positions of UE_Ds which are close to BS have low goodput due to the limitation of P_D which reduces the achieved Γ of the UD2D communication link, especially at positions close to UE_Cs. However, the SOLinA optimizes the performance (via ADPSO algorithm) by decreasing the L and M according to the upper limit of P_D so as to achieve high f_t which achieves high goodput, compared to PSO algorithm. Also, the role of MQL at these position is important to learn the f_C which has the lowest cellular activity (while they have similar interference level) by increasing the rwd at every successful transmission. This leads to increase the q of such sub-channel and propose it after every hand-offs.

However, four positions in the cell still have low goodput, compared to other positions, due to the intra-cell interference from the close UE_Cs, as shown in Fig. 6.6 (a) and (b). These positions are:

- Position A: d_{BSD} is 2000 m and d_C is 3000 m.
- Position B (d_{BSD} is 4000 m and d_C is 5000 m)
- Position C (d_{BSD} is 6000 m and d_C is 7000 m)
- Position D (d_{BSD} is 8000 m and d_C is 9000 m)

Figure 6.7 shows a comparison of the goodput achieved using PSO and SOLinA algorithms at these positions which have similar interference levels. This makes any heuristic search technique inefficient to select the best sub-channel due to the dependence on the values $Prob_i$ and I_C which are almost similar for all the sub-channels. However, the MQL

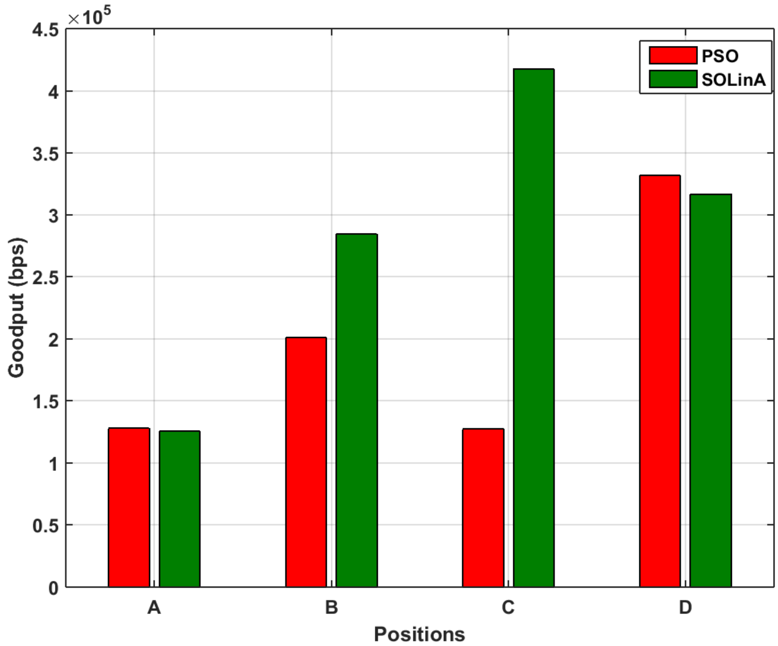

Figure 6.7: Comparison of achieved goodput of UD2D communication using PSO and SOLinA algorithms at different positions in the cell.

in SOLinA algorithms plays an important role in determining the best sub-channel to access by updating the reward rwd, as mentioned above.

6.4 Summary

In order to evaluate the performance of the proposed algorithm in Chapter 5, a simulation scenario which includes cellular activity has to be performed. The applied simulation scenario uses defined models related to propagation, interference, path loss and $\mathrm{UE_C}$s activity models. The simulation scenario has studied the impact of geographical positions of the entities in the cell (BS, $\mathrm{UE_C}$s and $\mathrm{UE_D}$s) on the performance of UD2D communication using SOLinA algorithm. To evaluate the performance efficiently, a fair comparison has been performed with PSO algorithm to adapts the link of UD2D communication.

In general, the results of simulation scenario show that the performance of UD2D communication is improved (in term of goodput) at positions far from both BS and $\mathrm{UE_C}$s due to low impacts of: i) intra-cell interference (from $\mathrm{UE_C}$s); and ii) limitation of I_C and Γ_C. These impacts are increased at position close to BS, $\mathrm{UE_C}$s or both.

According to the results, the SOLinA algorithm outperforms the PSO algorithm in the goodput at positions close to UE_Cs and BS, as well as far from them. The reasons behind these improvements are:

- the ADPSO algorithm in SOLinA attempts to conquer the local optima problem by jumping between different positions in the search space to find better solution (according to Eq.5.10). This leads to improve the achievable Γ which is compatible with higher M and L. Thus, transmitting longer frames with higher R_b improves the goodput of the link.

- the MQL algorithm learns the UE_C's activities and the best configuration set by applying rewards and penalties for each proposed action. By learning the best sub-channel to select (and applying the best configuration), the number of hand-offs is decreased increase the goodput.

However, the performance of SOLinA algorithm may degrade if it searches for a solution in a large N-dimension search space which may takes more time to achieve convergence. Also, the performance may degrade if the sub-channels have low deviation in their BUSY and IDLE periods, which slow down the learning process till it finds the best sub-channel to access. In such a case, the learning will not be useful especially if the data size is low which needs lower time to transmit.

Thus, the self-organization features in SOLinA algorithm assists to improve the UD2D link adaptation at different positions in the cell which improves the UD2D communication. It uses the sensing, searching, memorizing and learning techniques to determine the best configuration which improves the link performance of UD2D communication. Thus, it increases the goodput. By performing UD2D communication at these positions, the area used by the UE_Ds in the cell while meet the QoS requirements is increased.

7 Conclusion and Future Work

Contents

Applying data off-loading is a solution to improve the spectral efficiency of the cellular system which is proposed for the next years. However, some drawbacks with the licensed and unlicensed direct communication (D2D communication and UD2D communication) due to the used access paradigms which degrade the system spectral efficiency, consume more resources and consume more energy which leads to degrade the system performance. Thus, the contributions of this dissertation focus on proposing unconventional schemes for both D2D and UD2D communication that improve the system spectral efficiency and introducing a self-organized algorithm for link adaptation in UD2D communication to improve the link performance under dynamic radio environment.

7.1 List of Contributions

This dissertation introduces two major contributions for D2D communication to improve the cellular system performance. These contributions are described in the next subsections.

7.1.1 Analytical Model of System Capacity for D2D Communication

Applying D2D communication within the cellular systems has improved the spectral efficiency of the cellular system by offloading the data traffic from BS to direct communication. However, the impacts of cellular entities on the performance of D2D communication has not been studied deeply so as to define the weak points in D2D communication. Thus, in chapter 3 the spectral efficiency of the D2D communication has been modeled under different use cases to clarify the impacts of factors (such as SINR, interference margin and the geographical positions of the entities in the cell) on the D2D communication performance using different access paradigms.

The first contribution in Chapter 3 is defining mathematical models of the spectral efficiency of D2D communication which include the impacts of each factor on the D2D communication performance under different use cases. These models clarify the weak points in the underlay access paradigm which are related mainly to the intra-cell interference, SINR, interference margin from the cellular network side. Also, the path loss and the desired SINR are the factors from D2D communication side.

The second contribution is introducing a position-based hybrid access paradigm for D2D communication called Underlay-Overlay (UnOv) which merges the underlay and the overlay. The proposed access paradigm conquers the intra-cell interference at positions close to UE_Cs and BS, as well as improve the system spectral efficiency over the cell. A mathematical model for UnOv access paradigm has been presented which includes the activity of the cellular network in the resource blocks, the positions of UE_D pairs and UE_Cs, in addition to the aforementioned factors.

To evaluate the system performance within the proposed access paradigm, a numerical simulation has been performed to study the spectral efficiency of the system under the impacts of: i) D2D path loss; ii) SINR and interference margin of cellular system; iii) geographical positions of cellular entities in the cell; and iv) the number of UE_D pairs. The observations from the numerical simulation are:

- The UnOv access paradigm has less negative impact of intra-cell interference than the underlay access paradigm at positions close to UE_Cs and BS. Also, it has better system spectral efficiency close to the cell edge, compared to overlay access paradigm. These improvements are due to performing the decision of the proper access paradigms according to the geographical positions of the UE_Cs and UE_D pairs according to the best achievable system spectral efficiency in the cell. This leads to improve system spectral efficiency over different distances between the UE_D pairs, as well as the area used in D2D communication, compared to both underlay and overlay access paradigms.

- In multiple UE_D pairs use case, the UnOv paradigm optimizes the system spectral efficiency by selecting different access paradigm to each UE_D pair according to its position in order to achieve the maximum spectral efficiency of the system.

- The impacts of SINR and the interference margin of the cellular network varies according to the geographical positions of the UE_Cs and UE_D pairs in the cell. However, these impacts have been changed (the negative impacts have been reduced, while the positive impacts have been increased) in UnOv access paradigm due to the selecting the proper access paradigm for each UE_D pair according to its position in order to improve the system spectral efficiency over the cell, as well as the area used by D2D communication.

- Introducing multiple UE_D pairs in the cell using UnOv paradigm has a positive impactive on the system spectral efficiency till a certain number of UE_D pairs. However, introducing more UE_D pairs degrades the system spectral efficiency due to the high intra-cell interference between the UE_D pairs. In addition to number of UE_D pairs, the behavior of system spectral efficiency is negatively influenced by increasing the distance between the UE_D pairs.

7.1.2 Analytical Model of System Capacity for UD2D Communication

Although the integration of D2D communication improves the system spectral efficiency by reusing the resources, the spectrum band still has spectrum holes which reduces the spectrum utilization and the system spectral efficiency over time. On the other hand, the UD2D communication of unlicensed users over unlicensed spectrum has many drawbacks. Chapter 4 studies the integration of UD2D communication over licensed spectrum bands.

The first contribution of Chapter 4 is introducing mathematical model for the spectral efficiency of the system in presence of UD2D communication using different access paradigms related to cognitive communication. The introduced models depends on the position of UE-textsubscriptU pair, as well as the QoS of the cellular system, in determining the achievable spectral efficiency using each access paradigm.

The second contribution is introducing a hybrid access paradigm for UD2D communication called Underlay-Interweave (UI) which merges between the underlay and the interweave to conquer the intra-cell interference at positions close to UE_Cs in order to improve the spectral efficiency of the cellular system. A mathematical model for UI access paradigm has been presented which includes the activity of the cellular network in the resource blocks, in addition to the aforementioned factors (geographical positions, QoS requirements, etc.).

To evaluate the system performance within the proposed access paradigm, a numerical simulation has been performed to study the spectral efficiency of the system under the impacts of: i) UD2D path loss; ii) SINR and interference margin of cellular system; and iii) geographical positions of cellular entities in the cell. The observations from the numerical simulation are:

- The UI access paradigm has less negative impact of intra-cell interference than the underlay access paradigm due to working at OFF periods of the UE_Cs. However, it still suffer from the impacts of interference margin and SINR of the cellular network, the SINR of D2D communication.
- The CR technique provides degree of freedom to the UD2D communication by utilizing the OFF periods of the UE_Cs. While the probability of UE_C's activity is [0,1], the underlay-interweave access paradigm achieves a spectral efficiency of UD2D communication between underlay and overlay access paradigms. Also, underlay-interweave access paradigm outperforms the underlay and overlay in system spectral efficiency due to the best usage of spectrum sharing scheme.
- The impacts of SINR and the interference margin of the cellular network varies according to the geographical positions of the UE_Cs and UE_D pairs in the cell. However, it has been reduced in underlay-interweave access paradigm due to the opportunistic spectrum access which avoids intra-cell interference. Thus, the outage in CR-based UD2D communication is less at positions close to UE_Cs and BS, comparing to underlay access paradigm.

7.1.3 Self-Organizing Link Adaptation (SOLinA) Algorithm for UD2D Communication

Performing CR-based UD2D communication in cellular system requires a CE which adapts the link configuration of UD2D communication autonomously within any change in the radio environment in order to meet the desired QoS requirements. The role of the CE is: i) observing the surrounding environment; ii) deciding the best radio parameters to apply; and iii) learning the impacts of the applied decisions on the performance of the link. Different previous work have been implemented to perform autonomous link adaptation, however different drawbacks have been appeared such as slow convergence, low performance, high signaling overhead and high latency.

The contribution of Chapter 5 is proposing a self-organizing link adaptation algorithm (based on UI access paradigm) for autonomous UD2D communication without interfering the cellular system. The proposed algorithm consists of three entities: i) optimization entity which include a heuristic search- based algorithm called ADPSO to determine the radio parameters which optimize the performance under specific link objectives; ii) reasoning entity to use the previous actions under similar radio environment using CBR algorithm; and iii) learning entity to learn the activity over each sub-channels and the best action to apply using modified Q-Learning (MQL) algorithm.

To evaluate the performance of the proposed algorithm, simulation scenarios has been defined in chapter 6. It presents the applied models for propagation, path loss, interference and activities over the UL sub-band. The evaluation of SOLinA algorithm has been performed by studying the goodput which is related to the performance of the UD2D communication. The performance of SOLinA algorithm has been compared to PSO algorithm under similar scenario and simulation assumptions in order to perform a fair comparison.

The observations from the simulation scenario are:

- In general the performance metric (goodput), the UD2D communication are improved at positions far from both of $\mathrm{UE_C}$s and the BS due to the impacts of intra-cell interference (from $\mathrm{UE_C}$s), SINR and interference margin (from BS). However, these metrics have outages at positions between the BS and $\mathrm{UE_C}$s, as well as the $\mathrm{UE_C}$s (far from BS). Also, the no UD2D communication takes place at position close to BS due to the interference margin of BS.

- The SOLinA algorithm outperforms PSO algorithm in the goodput. The reason behind this improvement due to ADPSO algorithm which performs intensive search, compared to PSO, to conquer the local optima by jumping between different position in the search space in order to find better solution (set of radio parameters).

- The SOLinA algorithm suffers from long learning time (slow convergence) whenever the $\mathrm{UE_D}$s have similar interference level at all the sub-channels. In this case the MQL in SOLinA algorithm needs time learns $\mathrm{UE_C}$s activities at each sub-channel (the number of ACKs and Hand-offs). However, the close $\mathrm{UE_C}$s with similar activities over the sub-channels increase the convergence time due to long time required by SOLinA to decide the best sub-channel to access (which has lower activities).

- The convergence of the UD2D communication becomes fast if the interference levels at the sub-channels are different (the $\mathrm{UE_C}$s are at different distances from the $\mathrm{UE_D}$). Thus, the sub-channels with low interference level (used by far $\mathrm{UE_C}$s) can be accessed by $\mathrm{UE_D}$. To access such sub-channels, the SOLinA algorithm will depend only on ADPSO to find the best configuration parameter set to apply (very low number of Hand-offs and NACK using these resources).

7.2 Future Work

The main goal of this dissertation is to improve the system spectral efficiency by improving the performance of both D2D and UD2D communication in future cellular networks. The proposed idea for achieving this goal by improving the access paradigms of D2D and UD2D communications according to the geographical positions of the users (licensed and unlicensed) in the cell. Also, the developing a link adaptation algorithm for UD2D communication is another proposed idea in this dissertation to improve the goodput in the cell.

The dissertation presents a mathematical models for system capacity using D2D communication under different uses cases (single resource with single D2D pair and single RB with multiple D2D pairs) according to geographical positions of the cellular entities and their QoS requirements. Then it presents mathematical model of spectral efficiency using hybrid access paradigm for these use cases. It would be more interesting to study optimizing the spectral efficiency in Multiple RB with Multiple D2D Pairs (MRMP) using UnOv access paradigm. This step includes defining the relation between the different factors at each $\mathrm{UE_D}$ pair which affect the system spectral efficiency, as well as the number of served UEs (the $\mathrm{UE_C}$s and $\mathrm{UE_D}$s) in the cell. Also, defining an efficient scheme which solves such optimization problem is interesting because it can decide the proper mode of operation (cellular, orthogonal or non orthogonal mode) for each UE in the cell.

Also, the dissertation presents a hybrid access paradigm for UD2D communication over the licensed spectrum band to improve the system spectral efficiency. A mathematical model for this paradigm has been proposed to integrate CR within UD2D communication to compensate the single RB single UD2D pair use case. It would make more sense to introduce mathematical expressions of UD2D communication for other use cases (such as single resource with multiple UD2D pairs and multiple resources with multiple UD2D pairs). Also, defining algorithms to optimize the system spectral efficiency for multiple UD2D pairs use cases is important to achieve high number of satisfied UD2D communication pairs and improves the total spectral efficiency of the system.

Implementing self-organizing algorithm for link adaptation is another contribution in this dissertation to manage the link configuration of UD2D communication under dynamic radio environment. This algorithm uses objective functions to determines the radio parameters from PHY and MAC layers which meet the desired QoS requirements. However, including parameters related to routing protocols and modifying the link objectives to perform routing using UD2D communication can be very profitable. Also, studying the link performance of multiple UD2D communication has profit to design an algorithm which adapts the link of multiple UD2D pairs using CR technique in order to improve the system goodput, number of satisfied users and the resource consumption. Also, studying the multi-connectivity using different spectrum bands can be promising idea for low latency UD2D communication.

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Abbreviations

ACK .... ACKnowledgment
ACO .... Ant Colony Optimization
ADPSO .... Adaptive Discrete Particle Swarm Optimization
AI .... Artificial Intelligence
ANN .... Artificial Neural Network
AoA .... Angle of Arrival
BER .... Bit Error Rate
BS .... Base Station
C-Rx .... Cellular Receiver
C-Tx .... Cellular Transmitter
CBR .... Case-Based Reasoning
CCC .... Common Control Channel
CDF .... Cumulative Density Function
CE .... Cognitive Engine
CLE .... Clear Link Establishment
CLO .... Cross-Layer Optimization
CM .... Cellular Mode
CoI .... Cell of Interest
CR .... Cognitive Radio
CSI .... Channel State Information
D2D .... Device-to-Device
DL .... Downlink
DPSO .... Discrete Particle Swarm Optimization
DSA .... Dynamic Spectrum Access
ELS .... Elitist Learning Strategy
FDD .... Frequency Division Duplex
FLC .... Fuzzy Logic Control
GA .... Genetic Algorithm
Iw .... Interweave

KB .... Knowledge Base
MOOP .... Multi-Objective Optimization Problem
MQL .... Modified Q-Learning
MRMP .... Multiple RB with Multiple D2D Pairs
NACK .... Negative ACKnowledgment
NOM .... Non-Orthogonal Mode
OM .... Orthogonal Mode
Ov .... Overlay
PDF .... Probability Density Function
PSO .... Particle Swarm Optimization
PU .... Primary User
QoS .... Quality of Service
RB .... Resource Block
RBS .... Rule-Based System
RL .... Reinforcement Learning
RQLE .... ReQuest Link Establishment
RTS .... Request To Send
SDR .... Software Defined Radio
SINR .... Signal to Interference plus Noise Ratio
SOLinA .... Self-Oranized Link Adaptation
SRMP .... Single RB with Multiple D2D Pair
SRSP .... Single RB with Single D2D Pair
SS .... Singal Strength
SU .... Secondary User
TDMA .... Time Division Multiple Access
TSP .... Traveling Salesman Problem
UD2D .... Unlicensed Device-to-Device
UE .... User Equipment
UE_C .... Cellular User Equipment
UE_D .... Device-to-Device User Equipment
UE_D-Rx ...... UE_D Receiver
UE_D-Tx .... UE_D Transmitter
UI .... Underlay-Interweave
UL .... Uplink
Un .... Underlay
UnOv .... Underlay-Overlay

XCVR .... Transceiver